Key Information Extraction in Purchase Documents using Deep Learning and Rule-based Corrections

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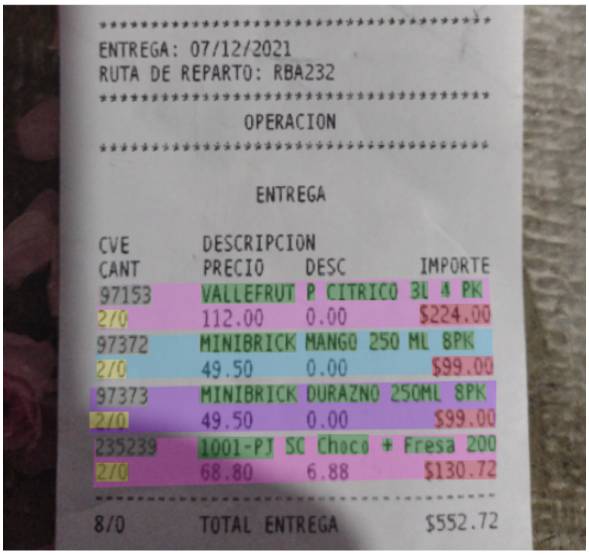
Abstract

Deep Learning (DL) is dominating the fields of Natural Language Processing (NLP) and Computer Vision (CV) in the recent times. However, DL commonly relies on the availability of large data annotations, so other alternative or complementary pattern-based techniques can help to improve results. In this paper, we build upon Key Information Extraction (KIE) in purchase documents using both DL and rule-based corrections. Our system initially trusts on Optical Character Recognition (OCR) and text understanding based on entity tagging to identify purchase facts of interest (e.g., product codes, descriptions, quantities, or prices). These facts are then linked to a same product group, which is recognized by means of line detection and some grouping heuristics. Once these DL approaches are processed, we contribute several mechanisms consisting of rule-based corrections for improving the baseline DL predictions. We prove the enhancements provided by these rule-based corrections over the baseline DL results in the presented experiments for purchase documents from public and NielsenIQ datasets.

1 Introduction

The intersection between NLP and CV algorithms is a key factor in systems that require processing visual and textual features. There are several use cases in the retailing industry in which this combination is typically applied, such as automated item coding (Arroyo et al., 2019), classification of promotions in digital leaflets (Arroyo et al., 2020) or the application of Visual Question Answering (VQA) to store observation systems (Arroyo et al., 2022), among others. In general terms, a great part of these use cases rely on KIE for automatically obtaining data of interest from varied sources related to images and documents. One of the main approaches based on KIE for retail and consumer measurement is focused on the automated recognition of data from purchase documents, such as receipts and invoices.



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ENTREGA: 07/12/2021
RUTA DE REPARTO: RBA232
************************************
              OPERACION
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               ENTREGA

CVE      DESCRIPCION
CANT     PRECIO    DESC      IMPORTE
97153    VALLEFRUT P CITRICO 3L 4 PK
2/0      112.00    0.00      $224.00
97372    MINIBRICK MANGO 250 ML 8PK
2/0      49.50     0.00      $99.00
97373    MINIBRICK DURAZNO 250ML 8PK
2/0      49.50     0.00      $99.00
235239   1001-PJ SC Choco + Fresa 200
2/0      68.80     6.88      $130.72
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8/0      TOTAL ENTREGA       $552.72
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Figure 1: Example of KIE in purchase documents from the NielsenIQ dataset. We can see entities tagged as product codes in gray, descriptions in green, quantities in yellow and total prices in red. Moreover, the regions corresponding to a same product jointly with their linked entities are marked in a blue to purple scale.

The information of interest commonly acquired by purchase decoding systems is associated with the purchased products printed in the documents to be recognized at item level, as depicted in Fig. 1. Here, there are several entities of text related to the characteristics of a purchased product that are generally extracted, such as the following ones:

- *Description*: textual specification for representing a purchased product.
- *Code*: unique numerical identifier of a purchased product.
- *Quantity*: total purchased units of the same product.
- *Price*: total value of all the purchased units from the same product.

In this paper, we propose a novel approach for KIE in purchase documents using DL and rule-based corrections. The presented DL architecture initially extracts the words contained in the document using OCR facilities. The recognized words jointly with the processed image are used as input of an entity tagging model based on Transformers and Convolutional Neural Networks (CNNs), which is able to predict the facts associated with the purchased products. Then, we compute a line detection method based on GNNs (Graph Neural Networks) with the aim of grouping all the text lines corresponding to a same product for entity linking. Finally, our pipeline applies some rule-based refinements to the previously predicted tags to correct possible inconsistencies.

We observed that standard DL proposals for entity tagging decrease their performance in complex purchase documents with low image quality, so false positives and false negatives commonly appear within the set of predictions. However, we know some specific business rules related to purchase documents for product descriptions, codes, quantities and prices that can be applied in post-processing, with the aim of enhancing the global accuracy of the system. In this way, we can take advantage of the patterns learned by DL and combine them with the human knowledge about the rules related to the purchase document decoding use case, so both can be applied in a complementary way to improve the quality of our whole solution.

In this regard, the main contributions derived from the research presented in this paper are the following ones:

- Design of a DL approach for KIE focused on purchase documents, which fuses NLP and CV in an architecture composed of OCR, entity tagging and product line grouping for entity linking.
- Definition of rule-based corrections in order to enhance the initial predictions given by the DL approach, demonstrating how pattern-based techniques can complement DL to improve performance.
- Presentation of a set of experiments in public and NielsenIQ datasets with the aim of validating our DL approach for KIE in purchase documents, jointly with the enhancements provided by rule-based corrections.

The contents of the paper are organized as follows: a review of the main state-of-the-art methods for KIE in document decoding is presented in Section 2. Our approach for KIE in purchase documents using DL and rule-based corrections is detailed in Section 3. The main experiments and results related to our DL proposal and the accuracy improvements of rule-based corrections are discussed in Section 4. The final conclusions associated with our research and some insights about future works are finally summarized in Section 5.

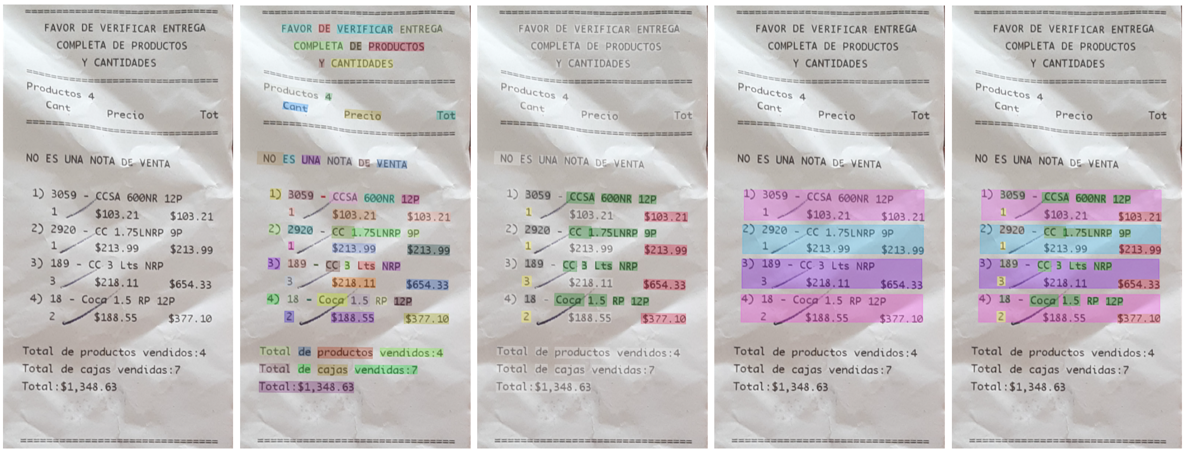
2 Related Work

The rise of DL has provided powerful tools to the fields of NLP and CV, which are the base of KIE systems focused on purchase documents decoding. This research line has also grown thanks to the proliferation of related public datasets, such as CORD (Park et al., 2019), SROIE (Huang et al., 2019) or FUNSD (Jaume et al., 2019). Moreover, companies working on retail intelligence also generate large amounts of data that are typically used for researching in real use cases, such as NielsenIQ.

In the intersection between NLP and CV, OCR techniques commonly represent the starting point for recognizing the text contained in a document or image. Methods based on OCR examine images pixel by pixel, looking for shapes that match the character traits. The state of the art in OCR comprises solutions that are open source and proprietary. Tesseract OCR is one of the most effective open-source approaches (Anwar et al., 2022). However, proprietary solutions such as Amazon or Google OCR are currently obtaining much better results in text recognition (Hegghammer, 2022).

Once the text is recognized, purchase document decoding systems typically need to understand certain parts or extract specific information. In this regard, the recent popularization of Transformers (Vaswani et al., 2017) and architectures such as BERT (Devlin et al., 2018) in the NLP community has provided new tools for achieving the desired results.

Among the different possibilities of text understanding, document decoding systems for purchase facts are commonly associated with entity tagging. This approach is applied with the aim of extracting specific product information in purchase documents, such as product description, code, quantity or price. Entity tagging is another state-of-the-art field that has been benefited by Transformers.



(a) Input. (b) OCR. (c) Entity tagging. (d) Prod. line grouping. (e) Output.

Figure 2: Main stages of our approach for KIE in purchase documents using DL and rule-based corrections. a) Input: initial data acquisition and image digitalization. b) OCR: detection and recognition of the words in the image. c) Entity tagging: identification of purchase facts of interest (e.g., product codes, descriptions, quantities, or prices). d) Product line grouping: identification of text lines and grouping by products of interest. e) Output: final predictions after rule-based corrections (if any). In this case, the diagram shows an example were DL was enough to properly predict all the tags, but we will depict specific cases along the paper in which rule-based corrections are carried out with respect to the original entity tagging predictions.

For instance, the architecture defined by PICK (Yu et al., 2021) is typically used in entity tagging systems, because its combination of Transformers to get text embeddings and CNNs to obtain image embeddings (He et al., 2016) provides one of the top performances in the recent literature. Another popular technique for entity tagging is LayoutLM and its different versions (Xu et al., 2020, 2021a; Huang et al., 2022), including an approach focused on multilingual capabilities (Xu et al., 2021b).

Apart from entity tagging, entity linking is also typically required to match each purchase tag with each respective product in the purchase document. Here, state-of-the-art techniques such as SPADE (Hwang et al., 2021) or BROS (Hong et al., 2022) propose end-to-end entity linking approaches. However, our proposal considers a method based on two stages, consisting of an initial entity tagging which is then linked by using line detection algorithms and rule-based heuristics for product lines grouping. For line detection, we take advantage of recent GNN proposals such as (Qasim et al., 2019) or (Carbonell et al., 2021).

Unfortunately, the state of the art does not consider a lot of solutions for correcting wrong entity tagging predictions, which is something typical in complex documents. For this reason, we propose novel rule-based corrections for improving automated entity tagging in purchase documents.

3 Our Approach

In this section, our whole pipeline proposed for KIE in purchase documents using DL and rule-based corrections is described. The core architecture builds upon DL in order to obtain the initial predictions for recognizing the text in the documents and tag words into varied categories from the different purchased products characteristics. Once these baseline predictions are provided by the DL pipeline, the implemented rule-based corrections are applied to refine the final output. We explain both DL and rule-based schemas with the aim of fully understanding the complementary solutions designed to extract the information of interest from purchase documents.

3.1 DL Architecture

The pipeline based on DL is composed of three main stages presented in Fig. 2 from input to output. These stages are basically OCR, entity tagging and product line grouping.

We explain the most common technical challenges for each stage along this section, jointly with their implementations mainly based on DL approaches. The goal is to understand how the learned textual and visual features are impacting the performance of the final system before checking how rule-based patterns can complement them to enhance the final output.

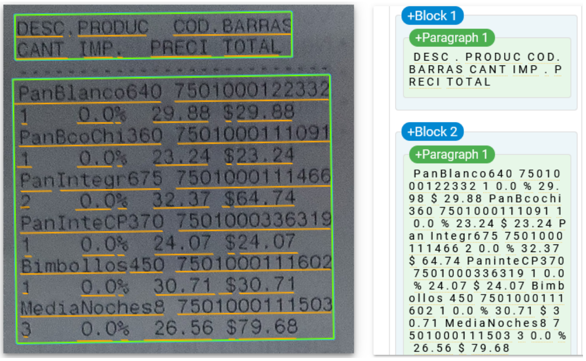
3.1.1 OCR

The proper selection of a robust OCR engine is crucial for the development of any document decoding system, because it is the bottleneck for the subsequent stages in the DL architecture.

OCR converts purchase images into machine-readable text data. The human visual system reads text by recognizing the patterns of light and dark, translating those patterns into characters and words, and then attaching meaning to it. Similarly, OCR attempts to mimic our visual system by using DL.

As discussed in Section 2, papers focused on benchmarking OCR engines such as (Hegghammer, 2022) have demonstrated that propietary solutions are currently yielding much accurate results than open-source proposals. Then, we decided to build upon the OCR provided by the Google Vision API[1], which provides some of the most remarkable results in text recognition. It must be noted that the goals of this paper are not focused on contributing a new OCR engine, so we decided just to apply Google Vision API features for recognizing text as a base tool for the rest of the stages implemented for KIE in purchase documents using DL.

The output obtained by the OCR service is composed of the recognized text over the images and the locations of the detected characters, words and paragraphs, as shown in the visual example presented in Fig. 3. This output is used as input of the subsequent stage for entity tagging in order to classify the different words into their corresponding categories related to the varied purchased products characteristics.



DESC . PRODUC COD. BARRAS CANT IMP . P RECI TOTAL

PanBlanco640 75010 00122332 1 0.0 % 29. 98 $ 29.88 PanBcochi 360 7501000111091 1 0.0 % 23.24 $ 23.24 P an Integr675 7501000 111466 2 0.0 % 32.37 $ 64.74 PaninteCP370 7501000336319 1 0.0 % 24.07 $ 24.07 Bimb ollos 450 7501000111 602 1 0.0 % 30.71 $ 3 0.71 MediaNoches8 7 501000111503 3 0.0 % 26.56 $ 79.68

Figure 3: Visual example of OCR processing using the Google Vision API over a purchase document. Image is focused on a section where purchased products are printed. The output shows the detected characters, words and paragraphs over the image and the recognized text.

3.1.2 Entity Tagging

KIE systems typically require algorithms to understand the recognized text and categorize some parts of it. In this sense, entity tagging is used with the aim of categorizing information of interest from purchased products, such as descriptions, codes, quantities or prices.

There are different proposals in the recent state of the art for computing entity tagging based on DL. In our pipeline, we follow an encoder-decoder architecture similar to the presented in works such as (Yu et al., 2021). Within this schema, text features are acquired by a Transformer and image features are processed by a CNN, as shown in Fig. 4.

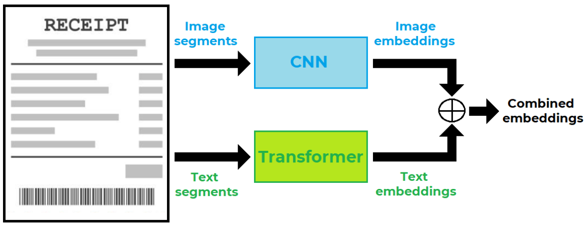


Figure 4: Base architecture for entity tagging using DL. Tranformers and CNNs are applied for extracting text and image embeddings, respectively.

The combined embeddings (CE) are obtained by fusing the image (IE) and text (TE) embeddings using an element-wise addition operation, as formulated in Eq. 1. Previously, IE and TE are outputted by the encoders into a vector derived from the CNN ($ie^{(x)}$) and Transformer ($te^{(x)}$) features respectively, as shown in Eq. 2 and Eq. 3. The encoders (θ) in each case are defined in Eq. 4 and Eq. 5, where $is^{(x)}$ represents the input image segments and $ts^{(x)}$ the corresponding text segments.

$$CE = IE \oplus TE \tag{1}$$

$$IE = [ie^1, ie^2, ..., ie^{N-1}, ie^N] \tag{2}$$

$$TE = [te^1, te^2, ..., te^{N-1}, te^N] \tag{3}$$

$$ie^{(x)} = \text{cnn}(is^{(x)}, \theta_{cnn}) \tag{4}$$

$$te^{(x)} = \text{transformer}(ts^{(x)}, \theta_{transformer}) \tag{5}$$

It must be noted that we decided to use a DL encoder-decoder architecture based on Transformers and CNNs because it is one of the most successful approaches in the state of the art, as we will discuss in the experiments presented in Section 4. However, our subsequent rule-based corrections over DL predictions could be adapted to any other entity tagging technique focused on similar DL schemas.

[1] https://cloud.google.com/vision

3.1.3 Product Line Grouping

Once entity tags are initially recognized for a purchase document, they are grouped by product to know their relationships and association with specific purchase characteristics. This entity linking is performed by applying a product line grouping step that uses DL and some grouping heuristics.

Firstly, the lines of the document must be individually detected. To do this, a GNN based on (Qasim et al., 2019) is implemented with the aim of connecting the different words previously extracted as entity tags of interest in a same line. This GNN proposes an architecture based on graph networks that combines the benefits of CNNs for visual feature extraction and graph networks for dealing with the problem structure.

After detecting the individual lines, some heuristics are applied to group the lines corresponding to a same product, as illustrated in Fig. 5. The steps of this grouping process are the following ones:

1. Take the first individual line detected (from top to bottom in Y axis) and check if there are product description entities. If not, continue searching until the grouping algorithm finds the first line with a product description.

2. Once the algorithm finds the line with product description entities, there are two options:

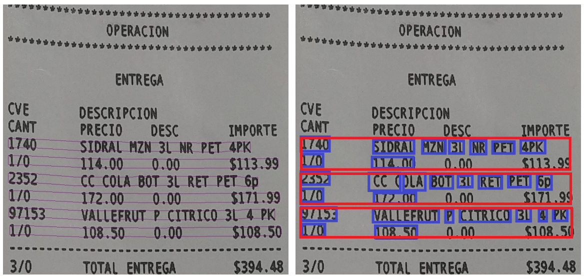
   (a) If the line also contains a product quantity and price (codes are not always available according to business rules), all the information of interest is located in that line and can be individually grouped.

   (b) If the line only contains description tags, go to step 3.

3. Check if the next line contains another description or any other tag, there are two options:

   (a) If there are only description tags, it means that the whole product description covers more than one line. The algorithm will search until it finds a line containing any other entity different from description before closing the group of lines.

   (b) If there are tags such as product quantity or price, the group of lines can be directly closed. Then, the algorithm takes the previously accumulated lines for the current product and combines their bounding boxes to obtain the final product line grouping.



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***********************************
             OPERACION
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              ENTREGA

CVE     DESCRIPCION
CANT    PRECIO     DESC        IMPORTE
1740    SIDRAL MZN 3L NR PET 4PK
1/0     114.00     0.00        $113.99
2352    CC COLA BOT 3L RET PET 6p
1/0     172.00     0.00        $171.99
97153   VALLEFRUT P CITRICO 3L 4 PK
1/0     108.50     0.00        $108.50
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3/0     TOTAL ENTREGA          $394.48
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(a) Line detection. (b) Product line grouping.

Figure 5: Visual example from line detection to product line grouping. On the left image, the individual lines detected by the GNN from entities of interest are represented in purple. On the right image, the final product line groups are depicted in red, jointly with the entity tagging words of interest in blue.

3.2 Rule-based Corrections

Current solutions for document decoding trust on DL for varied algorithms related to NLP and CV, as we previously reviewed in our architecture for KIE in purchase documents. Unfortunately, the high variety of formats, qualities and languages in these documents makes difficult to train models able to generalize to every situation. Then, we can expect some errors in the baseline entity tagging predictions provided by a DL pipeline. These errors are not always possible to correct, because in some cases the associated text is very difficult to recognize and understand. However, there are some other cases in which we can apply business rules and human knowledge to find and ameliorate DL errors in predictions.

It is possible to correct some of the missed elements in the initial tags (false negatives) and even the ones that are wrongly detected (false positives) to replace them with the correct ones. Product descriptions are the core of our product line grouping heuristics because they are generally the most accurate in automation and usually contain several words. In the proposed rule-based corrections for entities, we focus on tags that are commonly composed of only one word based on numbers, which are a typical source of issues in purchase document decoding. These entity tags are mainly product codes, product quantities and product prices. It must be noted that although we focus on these common purchase tags, the rule-based corrections presented in this paper could be adapted or updated for other purchase tags depending on the requirements of a specific use case.

3.2.1 Corrections in Product Codes

Product codes do not always appear as part of the product information in purchase documents. However, when they are included among these data, they are typically the highest integer number in a product line grouping, as can be seen in the example presented in Fig. 6. Then, in case we cannot find the product code with the initial DL-based entity tagging, we can re-check if it is available by applying the rule formulated in Eq. 6 and Eq. 7, where TW_{pr} is a vector composed of all the words ($tw_{pr}^{(x)}$) that are not tagged inside a specific product group. It must be noted that $code_{pr}$ will be only corrected if the number resulting from applying Eq. 7 is higher than the minimum integer value among all the remaining words that are not tagged from DL predictions.

$$TW_{pr} = [tw_{pr}^{(1)}, tw_{pr}^{(2)}, ..., tw_{pr}^{(N-1)}, tw_{pr}^{(N)}] \quad (6)$$

$$code_{pr} = \max(\text{integer}(TW_{pr})) \quad (7)$$

In this case, we just try to find the missing code for a product if it has not been previously detected in order to solve false negatives, but it could be also applied for correcting false positives from DL predictions if required. In that scenario, low confidences associated with DL predictions in entity tagging could help to find candidates to be corrected. However, we decided to fix only false negatives and trust on DL for the rest of predictions, with the aim of obtaining the highest benefit from both DL predictions and rule-based corrections, without an implicit dependency on confidence thresholds. In fact, this schema obtains a remarkable enhancement in performance according to the results presented in Section 4.2, without adding the extra complexity and possible issues related to also modifying explicit DL predictions. A similar way of correcting false negatives is proposed for product quantities and prices.

3.2.2 Corrections in Product Quantities

Product quantity is another entity tag typically printed in purchase documents that can be fixed in several cases during post-processing by applying rule-based corrections. In this regard, we must consider that this value usually represents an integer number close or equal to one.

According to the previous considerations, we can search for the lowest integer number in a product line grouping in case we did not initially find this tag with DL-based entity tagging, as depicted in the visual examples that are presented in Fig. 7.

More formally, the definition of the rule associated with this correction for missed product quantities is formulated in Eq. 8. It must be noted that $quantity_{pr}$ will be only corrected if the number resulting from applying Eq. 8 is lower than the maximum integer value among all the remaining words that are not tagged from DL predictions.

$$quantity_{pr} = \min(\text{integer}(TW_{pr})) \quad (8)$$

3.2.3 Corrections in Product Prices

Product prices are commonly represented by float numbers. In the use case exposed along this paper, we specifically tag the total prices per product, so it is expected to find the highest float number in these situations. Then, if DL predictions are not able to find a total price for a product line grouping, the rule-based correction formulated in Eq. 9 is applied to check if it is possible to find a word that is not tagged fulfilling these requirements.

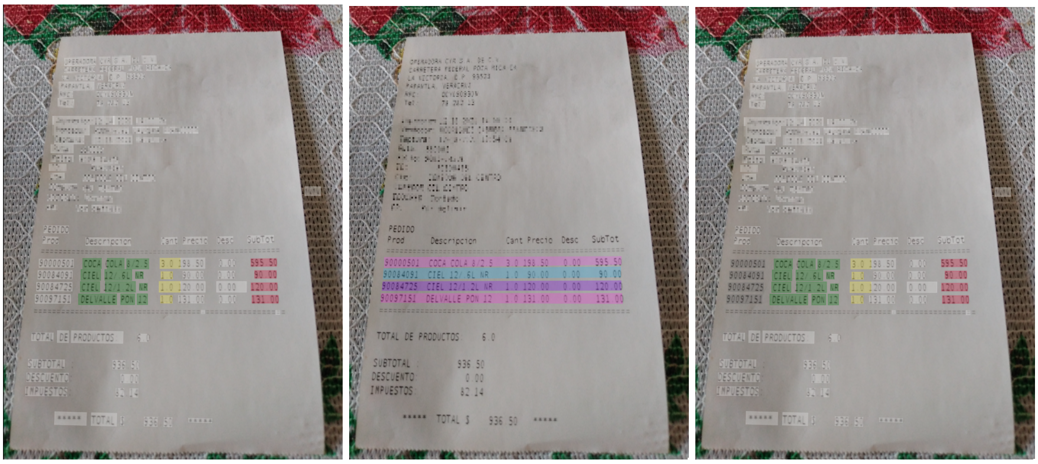
$$price_{pr} = \max(\text{float}(TW_{pr})) \quad (9)$$

4 Experiments

The main goal of the presented experiments is to verify the performance of our DL pipeline for KIE in purchase documents and demonstrate how rule-based corrections can increase final accuracy.

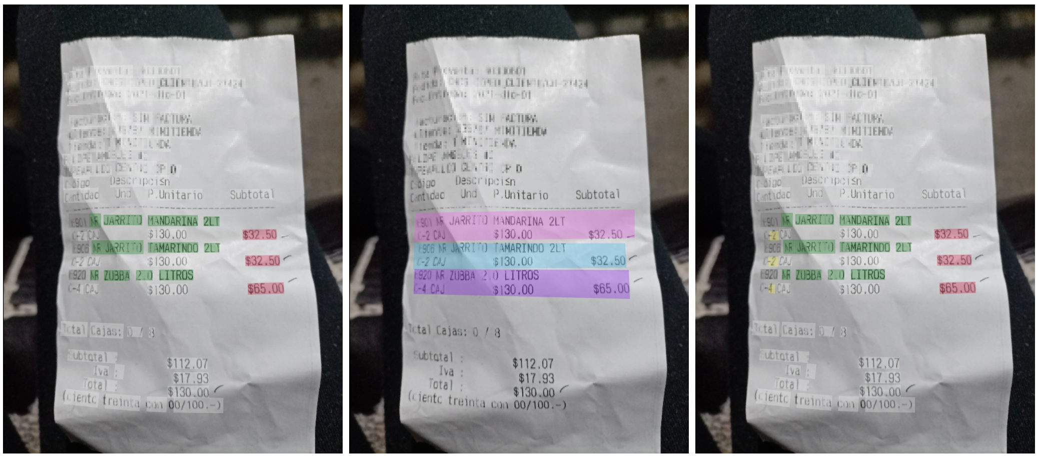
Initially, some public datasets are used to obtain performance metrics with the aim of comparing different entity tagging architectures with respect to our proposal based on an encoder-decoder built upon Transformers and CNNs, which is inspired by (Yu et al., 2021). The goal of this experiment is to validate that even a top state-of-the-art technique for entity tagging based on DL is far from perfection, so rule-based corrections can provide an added value for the most common error cases.

Besides, a dataset acquired by NielsenIQ is used to test the performance of the whole pipeline, including quantitative comparisons related to the improvements provided by rule-based corrections. Some qualitative examples from the NielsenIQ dataset can be reviewed in Figs. 6, 7 and 8.



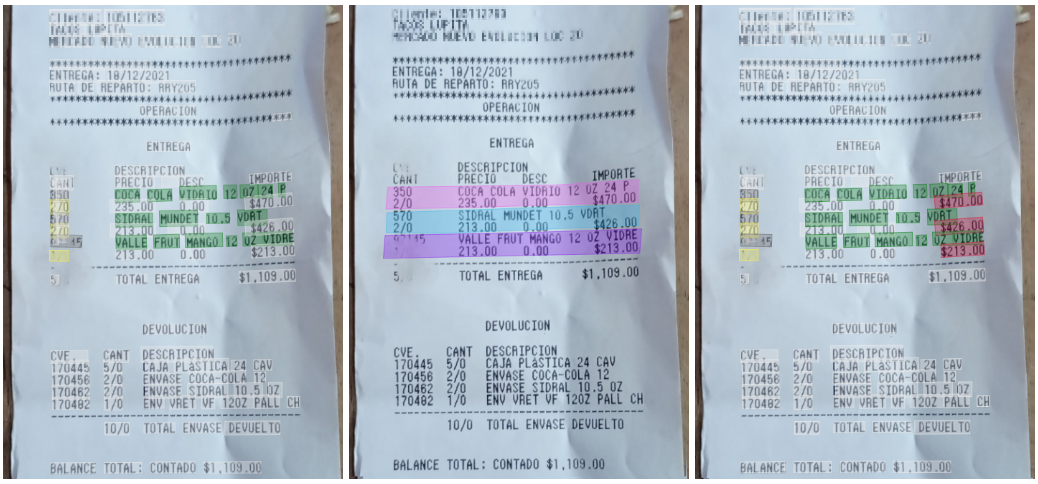
(a) Baseline entities. (b) Product line grouping. (c) Corrected entities for codes.

Figure 6: Visual examples of product code correction (in gray) based on rule-based heuristics.



(a) Baseline entities. (b) Product line grouping. (c) Corrected entities for quantities.

Figure 7: Visual examples of product quantity correction (in yellow) based on rule-based heuristics.



(a) Baseline entities. (b) Product line grouping. (c) Corrected entities for prices.

Figure 8: Visual examples of product price correction (in red) based on rule-based heuristics.

Method	Main reference	Parameters	f1-score		
			CORD	SROIE	FUNSD
BERT	(Devlin et al., 2018)	110M	89.7	91.0	60.7
LayoutLMv1	(Xu et al., 2020)	113M	94.7	94.4	78.6
LayoutLMv2	(Xu et al., 2021a)	200M	94.9	96.2	82.7
LayoutLMv3	(Huang et al., 2022)	133M	96.5	96.4	90.3
LayoutXLM	(Xu et al., 2021b)	345M	95.7	96.1	82.7
SPADE	(Hwang et al., 2021)	110M	91.5	93.2	71.6
BROS	(Hong et al., 2022)	139M	95.3	95.5	81.2
PICK	(Yu et al., 2021)	68M	95.2	96.1	82.5

Table 1: Comparison of state-of-the-art methods for entity tagging in the CORD, SROIE and FUNSD datasets.

4.1 Datasets

The main characteristics of the datasets used in our experiments are briefly reviewed here. The public datasets evaluated are CORD, SROIE and FUNSD. Apart from this, we also perform specific tests for our use case related to KIE in purchase documents by means of the NielsenIQ dataset.

4.1.1 The CORD Dataset

The COnsolidated Receipt Dataset (CORD)[2] is focused on receipt understanding for entity tagging and linking. The dataset includes 800 receipts for the training set, 100 for the validation set and 100 for the test set. A photo and a list of OCR annotations are included for each receipt. For entity tagging, there are 30 classes related to different information from shops and restaurants in Indonesia.

4.1.2 The SROIE Dataset

The Scanned Receipts OCR and Information Extraction (SROIE)[3] dataset is composed of a scanned collection from 1000 store receipts. 600 images are used for training and 400 for testing. Each receipt contains around about four key text fields for entity tagging. The text annotated in the dataset mainly consists of digits and English characters.

4.1.3 The FUNSD Dataset

The Form Understanding in Noisy Scanned Documents (FUNSD)[4] dataset includes documents containing forms. It is composed of 199 scanned documents, where 9707 semantic entities are annotated from 31485 words. 149 images are used for training and 50 for testing. There are 4 semantic entities: header, question, answer and other.

4.1.4 The NielsenIQ Dataset

Commonly, public datasets related to purchase document decoding include varied tags that are not always fitting the requirements of a particular use case. In our system, we want to specifically decode descriptions, codes, quantities and total prices per product. Then, we have used our own labeled data from NielsenIQ[5] considering the previously specified purchase tags to train and evaluate our full pipeline. As this dataset is composed of proprietary images, we can not publicly share them, but you can check their main characteristics in the example presented in Fig. 1. The images were captured with smartphones in different countries, with more than 10000 samples. Several challenges are considered due to the characteristics of data acquisition, such as different formats per retailer and country, multiple languages, or capturing quality for acquired images (e.g., varied resolutions, shadowing effects, blurring, oclussions, etc.).

4.2 Results

Based on the previously described datasets, we have processed several results regarding the state of the art in entity tagging and our whole KIE pipeline. The final goal is to measure the improvements in our DL system provided by the proposed rule-based corrections.

4.2.1 Entity Tagging Results

In Table 1, the base architectures of several approaches for entity tagging introduced in Section 2 are compared. We analyze the number of parameters for each approach and f1-scores in the public datasets introduced for document decoding (CORD, SROIE and FUNSD).

[2] http://github.com/clovaai/cord
[3] http://rrc.cvc.uab.es/?ch=13
[4] http://guillaumejaume.github.io/FUNSD
[5] http://nielseniq.com

Experiments for entity tagging	**f1-score**				
	Descriptions	**Codes**	**Quantities**	**Prices**	**Whole products**
With only DL	83.8	77.8	75.5	73.1	65.1
With rule-based corrections	**84.0**	**90.2**	**89.7**	**87.1**	**78.3**

Table 2: Results in the NielsenIQ dataset for entity tagging using only DL vs adding rule-based corrections.

Experiments for the whole pipeline	**f1-score**				
	Descriptions	**Codes**	**Quantities**	**Prices**	**Whole products**
With only DL	65.3	58.9	56.9	54.6	24.2
With rule-based corrections	**65.4**	**69.4**	**69.0**	**66.4**	**35.1**

Table 3: Results in the NielsenIQ dataset for the whole pipeline using only DL vs adding rule-based corrections.

As discussed in Section 3.1.2, we decided to apply an entity tagging schema based on an encoder-decoder built upon Transformers and CNNs. This architecture is inspired by the PICK algorithm described in (Yu et al., 2021). We made this decision supported by the results presented in Table 1, where PICK obtained one of the top performances in the three tested public datasets and using the lowest number of parameters (68M). This trade-off allows to have a high accuracy in DL predictions for entity tagging tasks jointly with light and efficient models. The average f1-score of LayoutLMv3 is the highest one and slightly better than the f1-scores obtained by PICK, but the number of parameters of LayoutLMv3 is almost double (133M). In any case, there is a margin of improvement regarding f1-scores for all the approaches that is expected to be reduced with our rule-based corrections, as will be experimented in the next section.

4.2.2 Whole KIE Pipeline Results

In these final experiments, we use the described NielsenIQ dataset for evaluating the improvements provided by our rule-based corrections with respect to the baseline DL predictions in KIE for purchase documents.

In Table 2, we present results for entity tagging including product descriptions, codes, quantities and prices. Besides, we also add a field named whole products, where a true positive represents a detected product with all its tags perfectly predicted. As can be seen, the rule-based corrections increase the performance of the mainly corrected tags, with an improvement in f1-score of about 13-14 points for codes, quantities and prices. These results clearly demonstrate how the combination of DL and rule-based approaches provides a higher performance in KIE for purchase documents.

With the aim of fully validating our proposal, we also present results for our whole pipeline in Table 3. This experiment includes f1-scores not only based on entity tagging, but also on OCR and product line grouping. We can see a general decrease in performance with respect to Table 2, especially because of the more restrictive metrics calculated in this case. In particular, OCR predictions must be fully matched with the ground-truth word to consider a true positive jointly with the rest of conditions, so low quality images are greatly affected by these errors. Then, we can appreciate other challenges in performance related to KIE apart from entity tagging. In any case, the results for the whole pipeline shown in Table 3 demonstrate again the improvements provided by rule-based corrections with respect to baseline DL predictions.

5 Conclusions and Future Work

The DL era has provided outstanding tools to solve complex problems in fields such as NLP and CV. Unfortunately, generalization and scalability to different use cases are still an open challenge.

In KIE for purchase documents, DL results can be degraded in cases associated with complex formats, low resolution or multilingual scenarios, among others. However, we have demostrated how rule-based corrections can complement DL architectures to enhance the performance of document decoding in the most difficult scenarios.

We have presented a basic set of rules based on business knowledge for correcting some common purchase tags, but more general rules could be explored in the future. Besides, further works could also include confidences application to rule-based corrections or similar post-processing rules for improving other KIE tasks such as OCR extraction.

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