Automated Drug-Related Information Extraction from French Clinical Documents: ReLyfe Approach

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Plan

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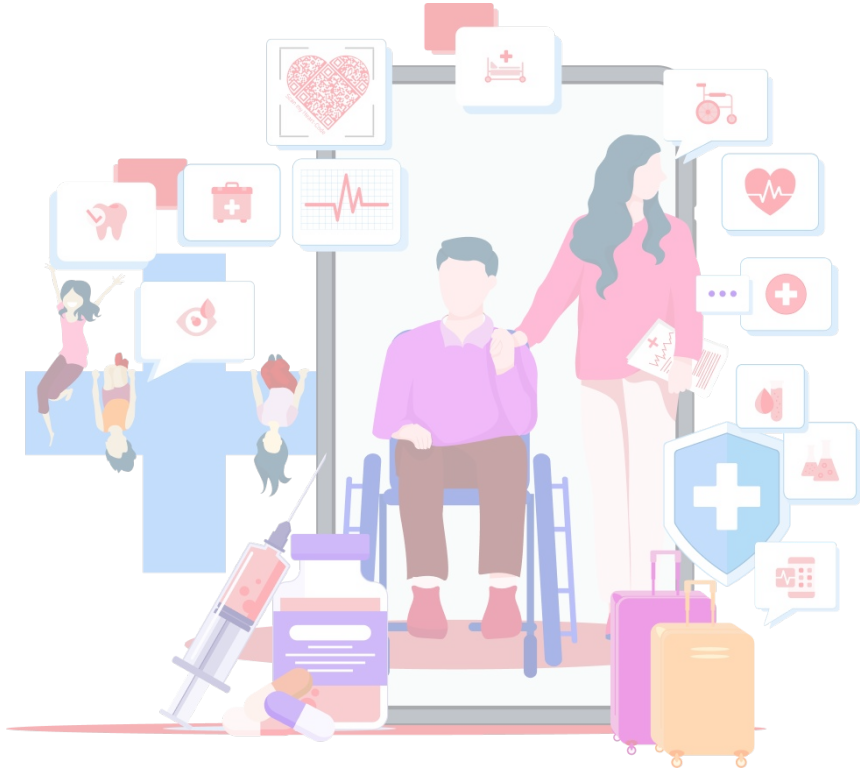
- Conclusion



Problematic

- **Problems :**
  - Lack of information doctors have about their patients.
  - Transferred documents from one doctor to another.
  - Wrong actions that are incoherent with the patient’s status.
  - Incompatibility between medication and their medical condition.
  - Healthcare systems do not have patient’s information gathered all in one place.
  - 80% of relevant clinical information exist only in an unstructured form.

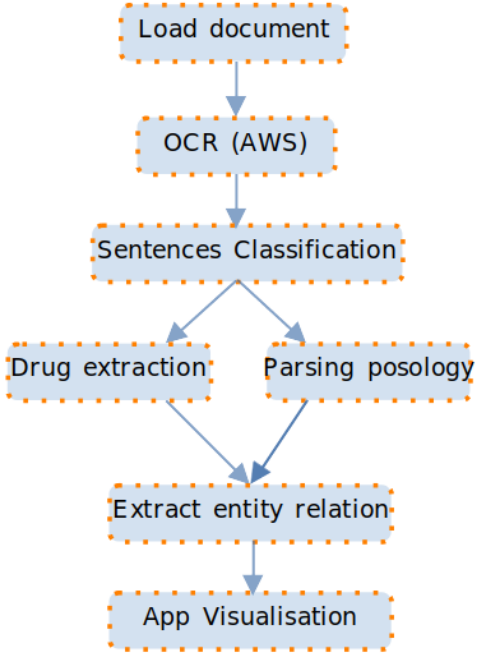
- **Solutions:**
  - Automatic Structuring of French medical prescriptions.
  - Clinical Natural Language Processing (NLP) and Named Entity Recongition (NER) model for the relevant medical information.

State-of-the-art

- **Related work:**
  - The majority of NLP research work on medical data has been carried out on texts/documents in English.
  - Since 2010, there have been less than five pertinent papers talking about the extraction of drug-related information from French clinical prescriptions.
  - Lexicon-based approaches use predefined lexicons or regular expressions to match parts of the text to recognize predefined entities (MedEx and MedXN).
  - NER model relying on a bidirectional long-short-term memory with conditional random fields (BiLSTM-CRF).
  - A conditional random field for the NER model along with a support vector machine extracting related entities combined with a rule-based context engine.

Materials and Methods

- **Method**
  - 5 main steps :
    - Optical Character Recognition (OCR).
    - Sentences classification model to differentiate between Drug, posology and private expressions.
    - Applying the two NER models (NER for the drug name, and the NER for its related information).
    - Connecting the drug to its related posolgy.
    - Finaly the display on our web application.



Materials and Methods

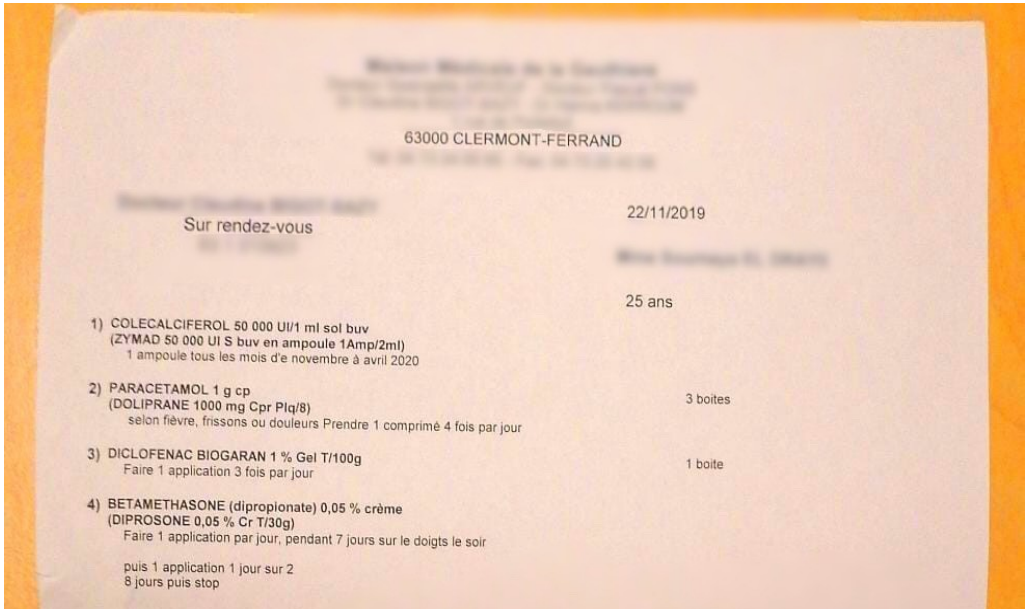
- **Data**
  - **Data for the NER models :**
    - 90% of the French prescription could be categorized into three types of formats.
    - It consists of : 100 prescriptions from 10 different cities and different clinics from 47 persons.
    - Each of them has at least five drug names followed by 1-3 sentences describing how it should be taken (posology).
  - **Data for the sentence classification model :**
    - 15000 drug names from the government public drug database.
    - We have generated 15000 synthetic posologies.
    - 15000 sentences carrying medical information, patient information, names, and all kinds of information that may be present in a prescription other than the drug and the posology.

Materials and Methods

- **Annotation Tools**
  - Prodigy: web application developed by Spacy library team.
  - It is a treaming display of all the document sentences one by one. The data scientist's role is to choose one of the predefined categories for each sentence as a label.
- **OCR**
  - We used the Aws service « Textract » to extract the text from the scanned prescriptions.
  - Documents were anonymized before being treated.
- **Text Pre-processing**
  - Unify the words format (remove the accents, lowercase, remove spaces, stop words,...)

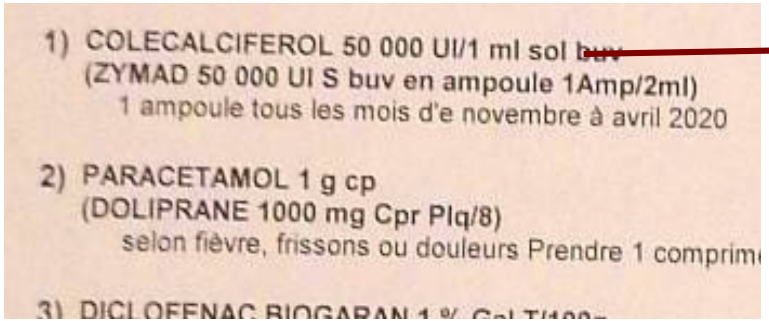
Materials and Methods

- **Sentences classification**
  - LSTM-Bi architecture is used to classify sentences into three categories :
    drug, posology, and useless sentences.
  - 95.23% Accuracy.



Materials and Methods

- **Drug detection**
  - Drug-matcher relied on a rule-based approach using the French Government drug databases.
  - Attach the detected drug to a unique international ID via the Vidal database.
  - If the first drug name does not exist in Vidal, we look at the second which is in parentheses.



Vidal output

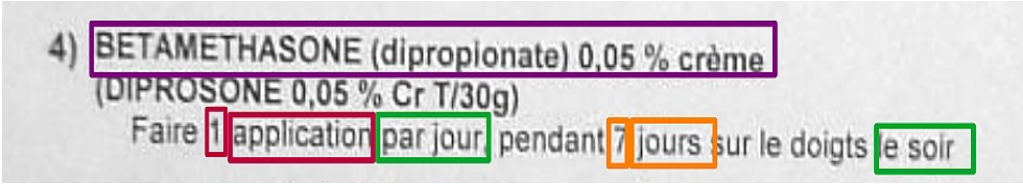

```
▸ vidal:categories : Array[1] ["VMP"]
▾ title :
    0 : "COLECALCIFEROL 50 000 UI/2 ml sol buv"
▸ link : Array[17] [{"rel":["alternate"],"type":["ap
▸ category : Array[1] [{"term":["VMP"]}]
▸ author : Array[1] [{"name":["VIDAL"]}]
▾ id :
    0 : "vidal://vmp/18301"
▸ updated : Array[1] ["2021-07-20T00:00:00Z"]
▸ summary : Array[1] [{"_":"colécalciférol * 50 000
▸ content : Array[1] [""]
```

Materials and Methods

- **Posology detection**
  - We employed the rule-based model from the NLP Spacy library to create the entity matcher.
  - We designed four matchers for the four different features we are looking for (dosage, frequency, duration, comment).

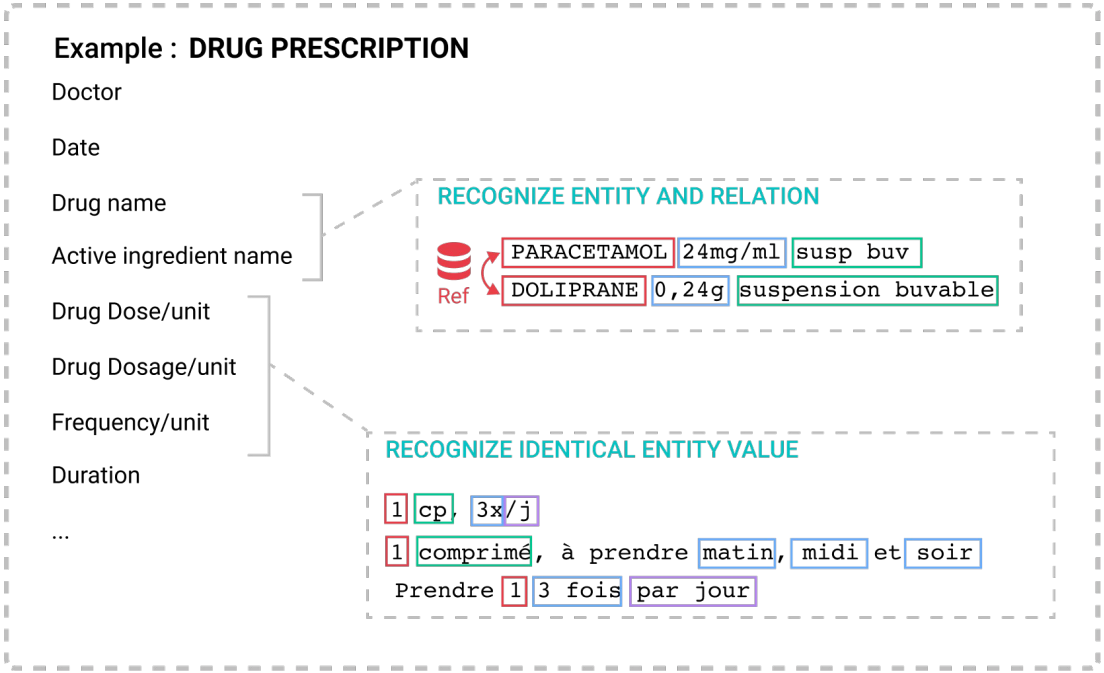
```
{"label":"DOSE","pattern":[{"LIKE_NUM": True}, {"LOWER" : {"REGEX":"(graduation[s]?)"}}]}
{"label":"DOSE","pattern":[{"LOWER": {"REGEX":"([\d]amp)"}, '_': {'position_token':True}}]}
{"label":"DOSE","pattern":[{"LIKE_NUM": True}, {"LOWER": {"REGEX":"(ampoule[s]?)"}}]}
{"label":"DOSE","pattern":[{"LOWER": "une"}, {"LOWER": {"REGEX":"(ampoule[s]?)"}}]}
```

rules created for the "dose matcher"



Materials and Methods

- **Drug-posology relation extraction**



Evaluation and Reuslts

- **Evaluation**
  - F1-Score :
    - An entity is considered a true-positive when it was annotated with the correct label.
    - False-positive when a token is falsely annotated with respect to each feature.
    - False-negative when it was not annotated at all, or it was annotated with the incorrect label.
- **Results**

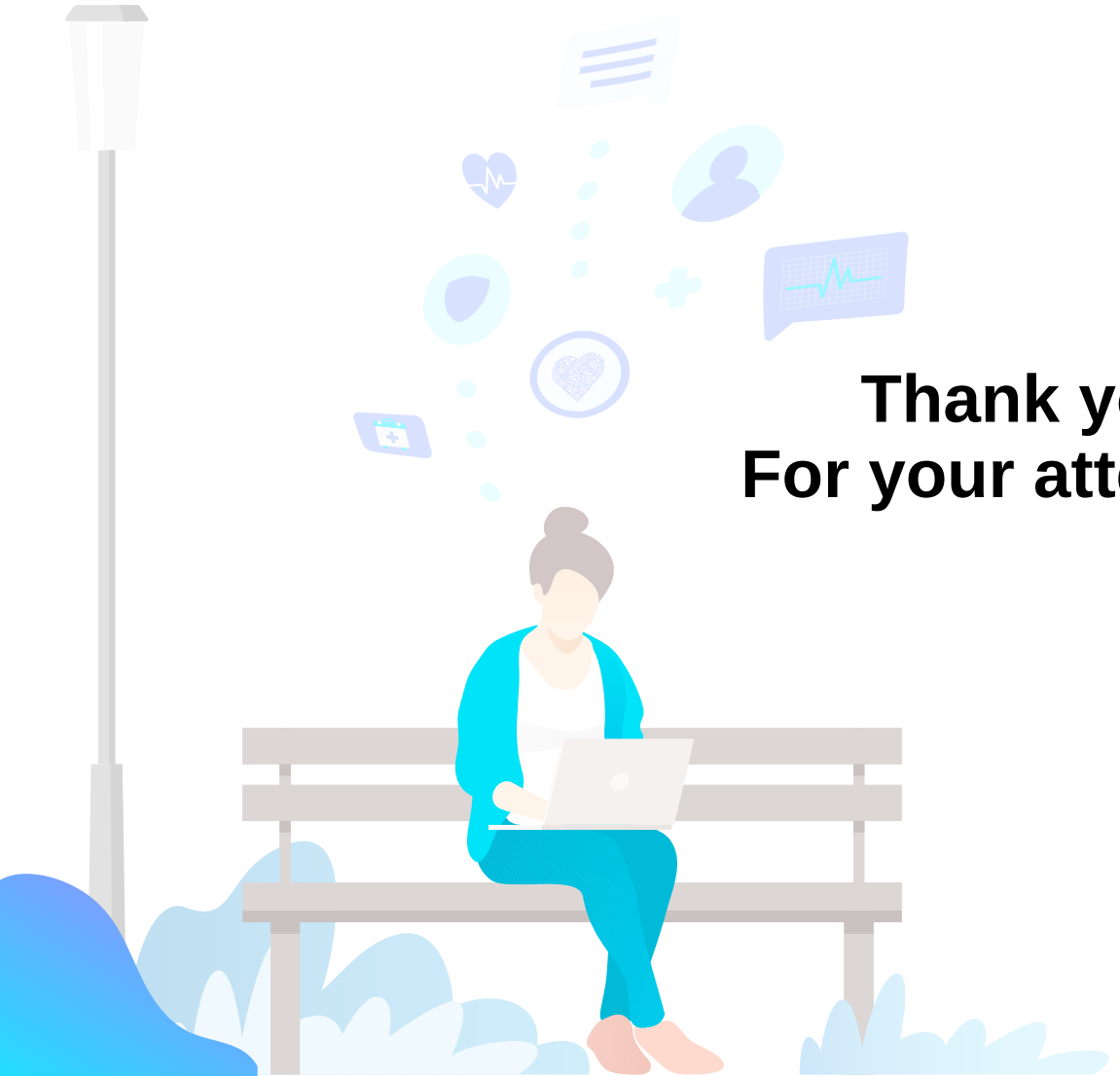
Label	F-measure	Precision	Recall
Drug name	94.33	100	89.33
Dose	93.91	100	88.52
Duration	94.91	98.24	91.80
Frequency	96.60	100	93.44
Comment	91.10	100	83.60

Evaluation and Reuslts

- **Results**
  - Add scanned document as a new treatment to your account.
  - Display the extracted entities in a web application in a very nice way and therefore will be useful for the user and the doctor.

Conclusion

- Real-time application to extract drug-related information.
- This work is one of the few that contributes to the French medical documents.
- Our approach is a series of methods concatenated together to achieve a high-performance system capable of coping with the constraints of real applications.
- Our algorithm based on human intuition and the sentence's geometric position.
- Theoretical and practical tests have proved the outperformance of our approach.
- Future Work :
    - Create a model based on a combination of Word embedding and a rule-based approach.



Thank you
For your attention