Automated Web Annotator of Biomedical Entities in Spanish language

Iza Iza, Josselyn Libelia

Morejón Corrales, Samiel Andrés

Departamento de Ciencias de la Computación

Carrera de Software

Artículo Académico, previo a la obtención del título de Ingeniero en Software

Msc. Uyaguari Uyaguari, Álvaro Danilo

19 de agosto de 2022

Latacunga

Automated Web Annotator of Biomedical Entities in Spanish language

Josselyn Iza
Departamento de Ciencias de la Computación
Universidad de las Fuerzas Armadas ESPE
Latacunga
Cotopaxi, Ecuador
jliza4@espe.edu.ec

Samiel Morejon
Departamento de Ciencias de la Computación
Universidad de las Fuerzas Armadas ESPE
Latacunga
Cotopaxi, Ecuador
samorejon@espe.edu.ec

Alvaro Uyaguari
Departamento de Ciencias de la Computación
Universidad de las Fuerzas Armadas ESPE
Latacunga
Cotopaxi, Ecuador
aduyaguari@espe.edu.ec

***Abstract*— In Natural Language Processing (NLP) and supervised machine learning, the scarcity of labeled corpora results in poor performance of machine learning models. In the medical domain, there are also fewer labeled corpora in Spanish than in English. We propose a method to identify biomedical entities in Spanish-language clinical texts, through automatic translation and word alignment, by translating the source text (Spanish) to the target text (English), then labeling the target text with automatic biomedical entity taggers, and finally projecting the biomedical entities from the target text to the corresponding text sections in the source text by means of word alignment generated in the translation process. This is done with the objective of annotating the source text with English language tools (automatic annotators). As a result, an efficient method capable of processing and annotating biomedical entities in the Spanish language with high precision is obtained, since it integrates several automatic annotators in a single web system.**

Keywords*— *natural language processing (NLP), word alignment, automatic annotation, web system, biomedical entity.

I. INTRODUCTION

Biomedical literature is one of the most important sources of knowledge for the advancement of research in the medical sciences. Especially in text mining, the development of new applications depends to a large extent on the existence of texts with annotated biomedical concepts. Although English is the most widely used language in this field, in recent years there has been a growing interest in natural language processing in languages other than English [1]. However, the availability of linguistic resources and tools for the correct treatment of texts other than English is insufficient.

This research focuses on the annotation of biomedical texts in the Spanish language, from which a tool was developed to detect entities in the biomedical field in the Spanish language. This web system has the ability to automatically translate, automatically detect medical terms and perform the labeling of the biomedical entities of the texts in Spanish, then the result will be displayed in Spanish language with their respective labels. Two automatic labeling tools have been chosen for this process: Metamap [2] for being one of the most widely used tools in the recognition of biomedical concepts of the Unified Medical Language System (UMLS). Metamap uses an approach based on natural language processing (NLP) and computational techniques and is one of the foundations of the National Library of Medicine (NLM) Indexing Initiative. System, which is being used for semi-automated and fully automated indexing of biomedical literature in the National Library of Medline [3]. However, this tool relies heavily on lexical resources and morphological analyses of English text [3]. The Healthcare Natural Language API (NLP) performs analysis of unstructured medical text and then generates a structured data representation of medical entities. It uses machine learning models to extract medical entities. Each text entity is extracted from the medical dictionary. To extract this level of medical statistics from the medical text, use the projects.locations.services.nlp.analyzeEntities method [4]. Once this process is completed, the identified medical entity is generated as a result, as well as the code in the NCI terminology system, including the confidence score assigned to the response.

These tools support the model created, in which the Microsoft Translator Api was used for text translation, which has a cloud-based neural machine translation service that belongs to the Azure Cognitive Services family of REST APIs [5]. To test the effectiveness of the automatic tagger, use was made of the Clinical E-Science Framework (CLEF) gold corpus [6], a manually annotated corpus of Spanish-language sentences in the health domain, because it focuses on extracting the main semantic entities from the text. By entity, it refers to some real world thing referred to in the text such as drugs, among others. CLEF contains the annotation methodology and reports the results of inter-annotator agreement. It incorporates the comparison between different text subgenres and annotators with different skills.

The content of this article is organized as follows. Section II describes related work that has been found in relation to the topic of the proposed article. Section III details the process and methods of realization of the automatic labeler. Section IV details the results obtained. Section V presents conclusions and future work.

II. RELATED WORK

Currently, annotation of biomedical concepts in non-English texts remains one of the most difficult research topics in NLP in the medical domain. In this regard, [2] presented a set of biomedical semantic annotation tools that are only available in English, because most biomedical resources, such as scientific articles, vocabularies and ontologies, are available in English. Based on this presented problem, it is necessary to conduct research on cross-linguistic semantic annotation of biomedical literature.

It has been possible to find some of the research done in this field, such as the creation of several models for the annotation of medical entities in languages other than English, where there are researches such as:

In [2], Cross-linguistic semantic annotation of biomedical literature: Experiments were carried out in Spanish and English based on the use of UMLSMAPPER considered as a pipeline for the annotation of medical entities. experiments in Spanish and English which is based on the use of UMLSMAPPER considered as a pipeline for the annotation of medical entities. The experiments carried out to evaluate the effectiveness of various methods for the automatic annotation of biomedical texts in Spanish are mentioned. The first approach is based on linguistic analysis of Spanish texts and annotation using information retrieval and conceptual disambiguation approaches. Then, a method uses a Spanish-English machine translation process to annotate English documents and transfer the annotations to Spanish. A third method uses a combination of the two procedures mentioned above. It was evaluated with Medline and EMEA, and considering the uncombined systems, all systems improve the baseline to an F1 score above 0.090. When performing notation transfer, UMLSMAPPER achieves the highest F1 score (0.630 and 0.634).

A computational ecosystem to support health knowledge discovery technologies in Spanish [7], in which he presents an annotation model using technology for the discovery of new health knowledge. It creates a free online infrastructure for the evaluation of automated systems and provides an analysis of many of the existing systems evaluated in this ecosystem.

Recognition of named biomedical entities with multilingual BERT [3], in this research a model based on PharmaCoTHER was performed and evaluated by a test set with BERT. Achieving a CRF score of 88% on development data and 87% on the test set with BERT.

Research has been found that creates architectures and tools that can be used to identify biomedical entities, among them: An integrated approach to biomedical term identification systems [9], shows the creation of an architecture for building biomedical term recognition systems, using the Freeling-Med tool. It combines several information sources and knowledge bases to provide biomedical term identification systems. The result is a system that performs the identification of medical concepts terms on any textual document written in Spanish, which performs a fine validation process on SciELO, Google Scholar and Medline resources. The Freeling-Med tool was used in the evaluation to compare performance. BSB (Biomedical Semantic Searcher) obtained an F1 score 22% higher than Feeling-Med, except in the OBJ group, where Freeling-Med obtained 60.68% and BSB 39.32%.

Automatic annotation of Spanish medical records with names of diseases, drugs and substances [10], which provides a tool based on lexical enrichment for the autonomous parser with medical terms extracted from dictionaries and ontologies. From the results obtained, it is clear that it is a tool that would aid data mining, with an F-measure of 0.90, and implies that the designed parser can automatically generate a reliable annotated corpus, among other pattern knowledge tasks in the biomedical domain.

In recent years, new research has emerged within the field of Bioinformatics, which has allowed the advancement of the state of the art. In which we find researches such as:
[11] is based on the DOI (Digital Object Identifier) code of some Medline citation editors. Using this approach, they constructed a parallel Spanish/English corpus (ENES). This shows that most sentences are correctly aligned with a mean score of 0.6232 F. Freeling-Med [12] performs Automatic Medical Record Annotation in Spanish with disease, drug and substance names, achieving a score between 90% and 92% although it is very high. The tool works with dictionaries of diseases and drugs in Spanish. The problem is that in the medical context there are not many dictionaries available in Spanish, and if these terms cannot be added, the tool will not be able to recognize them. The impact of simple feature engineering on multilingual medical NER [8] focuses on entity recognition in the clinical domain for three languages: English, Swedish and Spanish. For English and Spanish, they used Freeling-Med for lemmatization, POS tagging and annotation of Snomed CT concepts. For Swedish, they used Stagger. The results obtained are shown in measure F, where we obtained by adding features based on POS tagging in English 61.90%, in Swedish 65.55% and in Spanish 70.01%.

In contrast the other research mentioned in this section, this research presents a method that consists of different phases such as the translation of the Spanish texts into English and the alignment of words, the labeling of entities and the projection of the labeled entities into the Spanish language. This method differs from the other research reviewed since in this one a translator will be used to provide the word alignment in order to make use of it to perform the projection to the Spanish language. In addition, the different characteristics of entity labeling tools are analyzed, since they use different approaches to analyze unstructured medical text (heuristic searches and supervised learning models), to make use of them and subsequently combine the tools to improve entity labeling. An analysis of the performance of the tools is presented when a conventional translator is used for the translation of the text, as a loss of constancy during translation is evident, which generates a small loss of efficiency.

III. Systmen and Methods

In this research we make use of two biomedical text annotation tools (Healthcare Natural Language Api and Metamap), in order to increase the quantities of medical concepts to be recognized by the system.

The rest of this section describes in detail each of the processes and tools used for the recognition of biomedical entities in the Spanish language.

A. *Transfer of entities in the English language to the Spanish language*

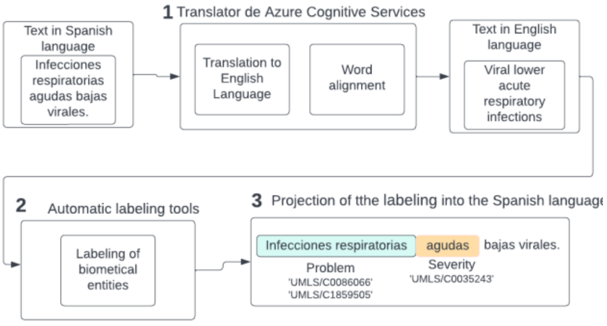

Fig. 1. Process diagram for labeling biomedical entities in medical texts.

A machine translation tool that incorporates word alignment was used. Therefore, this process consists of the following steps:

1) *Translation of Spanish texts into English and word alignment.*
2) *Automatic labeling of the text in English.*
3) *From the alignment, the labels obtained are projected to the original Spanish texts.*

a) Machine translation and word alignment: A machine translation was performed, for which the cloud-based neural machine translation service that is part of the Azure Cognitive Services family of REST APIs was used. This translation method incorporates word alignment, the alignment object with a single string property called proj, which assigns the input text to the translated text. Alignment information is only performed when the in-cludeAlignment request parameter is true. The alignment is returned as a string value with the following format:

[[SourceTextStartIndex]: [SourceTextEndIndex] [TgtTextStartIndex]: [TgtTex-tEndIndex]]] [13]. A colon separates the start and end indices, a hyphen separates languages, and a space separate word. A word may be aligned with none, one or several words of another language, and aligned words may not be contiguous. If no alignment information is available, the alignment element is empty [5]. This alignment can be seen in Table 1.

TABLE I. WORD ALIGNMENT OPERATION

Spanish Phrase	English Phrase	Alignment		
		Positions	Spanish	English
En pacientes menores de 16 años.	In patients under 16 years of age.	0:1-0:1	En	In
		3:11-3:10	pacientes	patient
		13:19-12:16	menores	under
		21:22-27:28	de	of
		24:25-18:19	16	16
		27:31-21:25	años	years
		27:3-30:33	años	years

b) Automatic labeling of biomedical entities: The text provided by Microsoft Translator already in the language is entered into the two automatic labeling tools (Metamap and Healthcare Natural Language Api).

In the Metamap tool, which uses a heuristic search approach, the evaluation function is used to calculate the measure of the quality of the match between a phrase and the metathesaurus candidate. The result is normalized to a value between 0 and 1,000, where 0 indicates no match and 1,000 indicates a perfect match.

The labeling process in the Healthcare Natural Language Api, we pass the already translated text, where machine learning models are used to extract medical entities. Each text entity is extracted from the medical dictionary. To extract this level of medical statistics from the medical text, using the projects.locations.services.nlp.analyzeEntities method [4]. Once this process is completed, the response is the entity with the code based on the NCI terminology system and includes the confidence score assigned to the response.

c) Projection of the labeling into the Spanish language: The algorithm initially collects all the phrases or words that have been recognized by the automatic taggers. We then group these texts with the initial English positions given by the taggers, and calculate the size of each word. how many text spaces each word has. With the positions we have for each word we add the calculated size to have the final position of the word. Having this, we look for that position in the alignment that we have in the translator, finding the position in English so that it returns us the position in Spanish. In this way we can obtain the biomedical entities labeled in the Spanish language. The final process can be seen in Figure 2, where the green color represents English and the blue color represents Spanish.

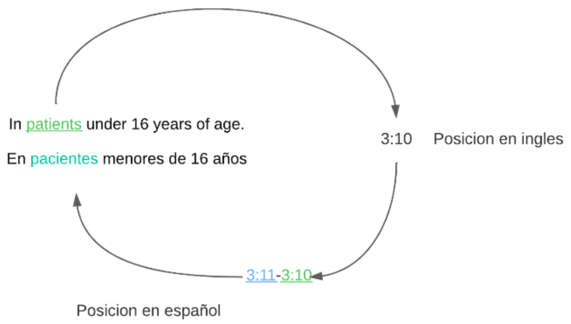

Fig. 2. Operation of the English to Spanish projection.

d) Validation: For validation of the annotator, the CLEF multilanguage gold corpus [6], which has biomedical concepts manually tagged and reviewed by health professionals, was used. In our case, we used the Medline and EMEA sections of the CLEF in English and Spanish.
Within these versions we can find the same phrases with their codes and labeled entities, but this in the two versions that would be Spanish and English, as shown in Table 2.
To perform the tests, we applied our annotator in the two sections (Medline, EMEA) in the Spanish language and the result of our annotator we compared it with the Spanish versions, in which it has inside the labels recognized and manually labeled by professionals. The results are detailed in Section IV, this based on the percentages of coincidence with the medical entities obtained in each of the tools.

TABLE II. CONTENTS OF THE ENGLISH AND SPANISH VERSIONS OF THE CLEF CORPUS

Spanish Phrase	English Phrase	Entities		Codes
		Spanish	English	
Tumores óseos benignos de nariz y senos paranasal es en la infancia. Revisión de casos en el Hospital Infantil de México	Benign bone tumors of the nose and paranasal sinuses in childhood. Review of cases in the Hospital Infantile of Mexico	nariz	nose	C0028429
		nariz	nose	C1278896
		senos paranasales	paranasal sinuses	C0030471
		Hospital	Hospital	C0019994
		México	México	C0025885
		Tumores óseos benignos	Benign bone tumors	C0684516

e) Web System: In this study, we created a web system using the Django Framework that supports the Python language where the system for the recognition and projection of entities from English to Spanish was created as shown in Fig. 3

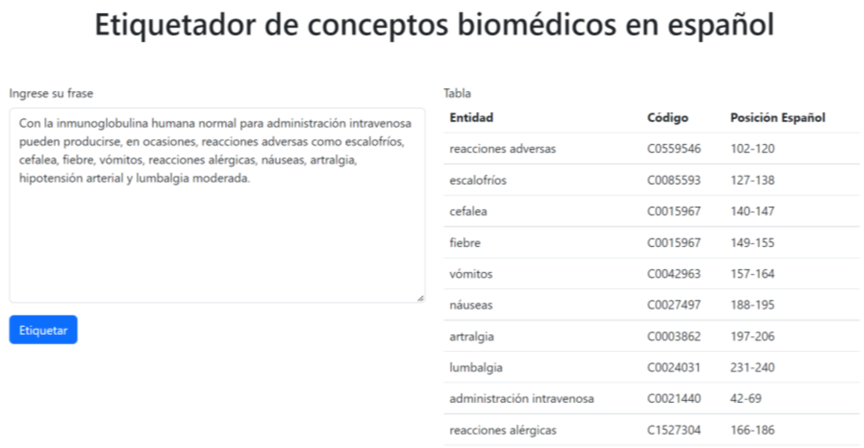

Fig. 3. Web system for tagging biomedical entities in Spanish

IV. RESULTS

As noted in the validation section d, we used the CLEF gold corpus for testing. In the Spanish sections, we pass the sentences to the translator, which then passes the translated English sentences to the tools Healthcare Natural Language Api and Metamap. In the English sections, we pass sentences directly to the tools Healthcare Natural Language Api and Metamap to assess the impact of using translation in the labeling process.

A. *Effectiveness of the automatic labeler*

To test the effectiveness of our annotator, we used a combination of automatic biomedical entity annotation tools (Healthcare Natural Language Api and Metamap) evaluated with two corpora, for which we used the EMEA [14] corpus segments, which was elaborated from PDF documents of the European Medicines Agency, and the Medline [14] corpus, which is composed of annotations with disease mentions.

TABLE III. LABELER RESULTS COMBINING THE TWO TOOLS (HEALTHCARE NATURAL LANGUAGE API AND METAMAP)

Corpus	**Results**	
	Tagged with combination of tools	***% of effectivenes ss***
Medline	166/316	52.53%
EMEA	237/430	55.11%

Table 3 shows the results obtained from the automatic tagger on the section of the Medline corpus, with a labeling result of 166 out of 316 total medical entities, which presents 52.53% effectiveness. As for EMEA, it can be seen that it recognizes 237 out of 430 total medical entities, resulting in 55.11% effectiveness, which is competitive with the averages found in the state of the art.

These results were obtained by combining the two automatic labeling tools (Api and Metamap) resulting in better entity labeling, as the two tools label better in different cases.

TABLE IV. ENTITY RECOGNITION TOOLS LABELING

Phrase	**Combination of Automatic Labeling Tools**			
	Entity	***Code***	***Healthcare Natural Language Api***	***Metam ap***
Supranuclear gaze palsy following extracorporea l surgery with induced hypothermia. Report of two cases.	Supranucle ar gaze palsy	C1720037	1	1
	Induced hypothermi a	C1301797	0	1
	Surgery	C0543467	0	1
	Induced hypothermi a	C0020674	0	1
	Report	C0700287	0	1

Table 4 shows the combination of the tools where "1" represents that it did find the entity and "0" represents that it did not find the entity, giving a better result since Metamap can tag more complex words and longer phrases, on the other hand Healthcare Natural Language Api can tag simple words and shorter phrases, which can be a great advantage since the longer the phrase can lose the sense of what you want to express, so API handles this easier than just separating the complex phrases into separate entities.

B. *Effectiveness of labeling tools.*

For this purpose, the sections of the translated EMEA and Medline corpora of the CLEF corpus were labeled separately. The best percentages of effectiveness obtained as a result of tagging the texts using the tools (Healthcare Natural Language Api, Metamap) are shown in bold.

TABLE V. RESULTS OF THE LABELING TOOLS (HEALTHCARE NATURAL LANGUAGE API AND METAMAP).

Corpus	Results	
	Biomedical entity labeling tools	***% of effectiveness***
Medline	Healthcare Natural Language Api	27.53%
	Metamap	**59.49%**
EMEA	Healthcare Natural Language Api	36.04%
	Metamap	**53.74%**

Table 5 presents the results obtained when evaluating each of the tools (Healthcare Natural Language Api and Metamap). It can be seen that the Api Healthcare Language has 27.53% and 36.04% effectiveness compared to Metamap which achieves 59.49% and 56.74% effectiveness. There is a big difference between them, so it can be deduced that although Healthcare Natural Language Api is a new tool with machine learning for predictions, Metamap is still one of the most effective tools, even though it makes its annotation based on dictionaries and other traditional linguistic techniques

TABLE VI. SEMANTIC TYPES FOUND IN THE EMEA AND MEDLINE CORPUS.

Identifier	Semantic Types
	Label
ANAT	Anatomy
CHEM	Chemicals & Drugs
DEVI	Devices
DISO	Disorders
LIVB	Living Beings
OBJC	Objects
PHEN	Phenomena
PHYS	Physiology
PROC	Procedures

Table 6 shows the semantic types found in the EMEA and MEDLINE corpora, respectively, with their identifier and the label referred to.

TABLE VII. LABELER RESULTS BY TYPE USING THE MEDLINE CORPUS(HEALTHCARE NATURAL LANGUAGE API)

Type	Healthcare Natural Language Api		
	Found	***Total***	***%Found***
ANAT	17	41	41.46%
CHEM	10	28	35.71%
DEVI	1	3	33.33%
DISO	36	109	33.02%
LIVB	5	41	12.195%
OBJC	0	3	0.0 %
PHEN	1	6	16.66%
PHYS	1	15	6.66%
PROC	17	63	26.98%

TABLE VIII. LABELER RESULTS BY TYPE USING THE MEDLINE CORPUS(METAMAP)

Type	METAMAP		
	Found	***Total***	***%Found***
ANAT	18	41	43.90%
CHEM	16	28	57.14%
DEVI	1	3	33.33%
DISO	73	109	66.97%
LIVB	30	41	73.17%
OBJC	3	3	100%
PHEN	1	6	16.66%
PHYS	9	15	60.0%
PROC	31	63	49.20%

Tables 7 and 8 show the effectiveness of labeling in each of the existing types in the UMLS, using the Medline section, which shows that the Metamap tool has a better effectiveness in each of the semantic types.

TABLE IX. LABELER RESULTS BY TYPE USING THE EMEA CORPUS (HEALTHCARE NATURAL LANGUAGE API)

Type	Healthcare Natural Language Api		
	Found	***Total***	***%Found***
ANAT	15	31	48.38%
CHEM	58	98	59.18%
DEVI	0	3	0.0%
DISO	65	151	43.04%
LIVB	1	47	2.12%
OBJC	0	8	0.0%
PHEN	0	6	0.0%
PHYS	0	20	0.0%
PROC	16	66	24.24%

TABLE X. LABELER RESULTS BY TYPE USING THE EMEA CORPUS (METAMAP)

Type	Metamap		
	Found	***Total***	***%Found***
ANAT	12	31	38,70%
CHEM	40	98	40,81%
DEVI	1	3	33,33%
DISO	68	151	45,033%

Type	Metamap		
	Found	*Total*	*%Found*
LIVB	35	47	74,46%
OBJC	3	8	37,50%
PHEN	3	6	50%
PHYS	7	20	35%
PROC	36	66	54,54%

Tables 9 and 10 shows the effectiveness of tagging in each of the existing types in the UMLS, using the EMEA corpus, which shows that the Metamap tool has a better effectiveness in DISO, LIVB, OBJC, PHEN, PHYS, PROC, on the other hand it can be seen that the Healthcare Natural Language Api has a greater effectiveness in ANAT and CHEM.

Finally, we performed a comparison of the labeling using the Microsoft translator and without using it, in order to evaluate the impact of using the translation, as mentioned at the beginning of this section. In order to show the best results, these will appear in bold.

TABLE XI. LABELER RESULTS PER TOOL WITH AND WITHOUT THE USE OF THE TRANSLATOR.

Corpus	Translator results		
	Biomedical entity labeling tools	***% Effectiveness with translator***	***% Effectiveness without translator***
MEDLINE	Healthcare Natural Language Api	27.53%	30.37%
	Metamap	59.65%	66.45%
EMEA	Healthcare Natural Language Api	36.04%	38.33%
	Metamap	56.74%	60.50%

Table 11 shows the effectiveness of each of the corpora for each labeling tool, using the Medline corpus, which shows that the use of the Metamap tool gives us the best effectiveness with and without using the translator. It also shows that when using the translator, we lose 6.8% of effectiveness when tagging entities.

TABLE XII. LABELER RESULTS BY COMBINED TOOLS WITH AND WITHOUT USE OF THE TRANSLATOR.

Corpus	Translator results		
	Combined biomedical entity labeling tools	***% Effectiveness with translator***	***% Effectiveness without translator***
MEDLINE	Healthcare Natural Language Api	65.50%	72.46%
	Metamap		
EMEA	Healthcare Natural Language Api	63.48%	69.53%
	Metamap		

Table 12 shows the results obtained by combining the two tagging tools, in the Medline corpus we get 72.46% which would be the best effectiveness without using the translator, when using the translator, we lose 6.96% of effectiveness. In the EMEA corpus we obtain 69.53% effectiveness also without using the translator, respectively we lose 6.05% effectiveness when using the translator.

TABLE XIII. LABELER SCORE VERSUS RELATED LABELERS' SCORES EVALUATED ON THE CLEF SEMANTIC GROUP.

Labeler	labelers evaluated by semantic groups		
	Semantic groups	***% Effective***	***language***
UMLSMapper	CLEF	62%	Spanish
MeSpeN	CLEF	47%	Spanish
Research	CLEF	52,53% - 55,11%	Spanish

Table 13 shows the results obtained in similar labelers versus with the results of the performance of the labeler generated in this investigation (research), where it can be shown that this one presents an effectiveness percentage of 52.53% - 55.11% when evaluated using the CLEF data set. This indicates that it is in a competitive range with respect to the other results shown in the table, having a range of difference between 5% to 6%.

V. CONCLUSIONS AND FUTURE WORK

This study presents the analysis and construction of an automatic tagger for biomedical entities in the Spanish language. Using cross-lingual and natural language processing techniques, the entities identified by the biomedical annotation tools (Metamap and Healthcare Natural Language Api) were translated from English into Spanish, resulting in biomedical entities labeled in Spanish. These have been validated on the CLEF gold corpus (EMEA and Medline sections) reaching a percentage of 52.53% and 55.11% of effectiveness respectively, which is in a competitive average with the percentages found in the scientific literature previously reviewed.

In addition, the effectiveness of the automatic annotators Metamap and Healthcare Natural Language Api on the CLEF gold corpus (EMEA and Medline Sections) was also evaluated at the general level and at the level of UMLS semantic types. It can be shown that each of these tools have a better labeling in different cases given in the texts as they use different approaches (Heuristic Searches and Supervised Learning Models). This structured knowledge could be used to create new machine learning models.

In addition, as future work, it is proposed to test the effectiveness by incorporating a translator focused on the medical field, to use it as a substitute for the Microsoft translator and then include the annotations in the translation process for the recognition of medical entities, thus satisfying the scarcity of resources. English language resources are used for this purpose, as this language has a high level of linguistic resources and "better quality".

VI. REFERENCES

[1] F. Giachelle, O. Irrera, y G. Silvello, «MedTAG: a portable and customizable annotation tool for biomedical documents», BMC

Med. Inform. Decis. Mak., vol. 21, n.o 1, p. 352, dic. 2021, doi: 10.1186/s12911-021-01706-4.

[2] *N. Perez et al., «Cross-lingual Semantic Annotation of Biomedical Literature: Experiments in Spanish and English», Bioinformatics, p. btz853, nov. 2019, doi: 10.1093/bioinformatics/btz853.*

[3] *K. Hakala y S. Pyysalo, «Biomedical Named Entity Recognition with Multilingual BERT», en Proceedings of The 5th Workshop on BioNLP Open Shared Tasks, Hong Kong, China, nov. 2019, pp. 56-61. doi: 10.18653/v1/D19-5709.*

[4] *Api Cloud Healthcare | Cloud Healthcare API, Google Cloud. https://cloud.google.com/healthcare-api?hl=es-419 (accedido 16 de julio de 2022).*

[5] *laujan, «¿Qué es Translator de Microsoft Azure Cognitive Services? - Azure Cognitive Services». https://docs.microsoft.com/es-es/azure/cognitive-services/translator/translator-overview (accedido 29 de junio de 2022).*

[6] *A. Roberts, R. Gaizauskas, M. Hepple, N. Davis, G. Demetriou, Y. Guo, J. Kola, I Roberts, A. Setzer, A. Tapuria and B. Wheeldin, «The CLEF Corpus: Semantic Annotation of Clinical Text», AMIA. Annu. Symp. Proc., vol. 2007, pp. 625-629, 2007.*

[7] *A. Piad-Morffis, Y. Gutiérrez, Y. Almeida-Cruz, y R. Muñoz, «A computational ecosystem to support eHealth Knowledge Discovery technologies in Spanish», J. Biomed. Inform., vol. 109, p. 103517, sep. 2020, doi: 10.1016/j.jbi.2020.103517.*

[8] *R. Weegar, A. Casillas, A. Diaz de Ilarraza, M. Oronoz, A. Pérez, y K. Gojenola, «The impact of simple feature engineering in multilingual medical NER», en Proceedings of the Clinical Natural Language Processing Workshop (ClinicalNLP), Osaka, Japan, dic. 2016, pp. 1-6. Accedido: 31 de julio de 2022. [En línea]. Disponible en: https://aclanthology.org/W16-4201*

[9] *P. López-Úbeda, M. C. Díaz-Galiano, A. Montejo-Ráez, M.-T. Martín-Valdivia, y L. A. Ureña-López, «An Integrated Approach to Biomedical Term Identification Systems», Appl. Sci., vol. 10, n.o 5, p. 1726, mar. 2020, doi: 10.3390/app10051726.*

[10] *M. Oronoz, A. Casillas, K. Gojenola, y A. Perez, «Automatic Annotation of Medical Records in Spanish with Disease, Drug and Substance Names», en Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications, vol. 8259, J. Ruiz-Shulcloper y G. Sanniti di Baja, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, pp. 536-543. doi: 10.1007/978-3-642-41827-3_67.*

[11] *A. Jimeno Yepes, É. Prieur-Gaston, y A. Névéol, «Combining MEDLINE and publisher data to create parallel corpora for the automatic translation of biomedical text», BMC Bioinformatics, vol. 14, n.o 1, p. 146, abr. 2013, doi: 10.1186/1471-2105-14-146.*

[12] *J. Ruiz-Shulcloper y G. Sanniti di Baja, Eds., Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications: 18th Iberoamerican Congress, CIARP 2013, Havana, Cuba, November 20-23, 2013, Proceedings, Part II, vol. 8259. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013. doi: 10.1007/978-3-642-41827-3.*

[13] *laujan, "Método de traducción de Traductor - Azure Cognitive Services." https://docs.microsoft.com/es-es/azure/cognitive-services/translator/reference/v3-0-translate (accessed Jul. 01, 2022).*

[14] *J. A. Kors, S. Clematide, S. A. Akhondi, E. M. van Mulligen, y D. Rebholz-Schuhmann, «A multilingual gold-standard corpus for biomedical concept recognition: the Mantra GSC», J. Am. Med. Inform. Assoc., vol. 22, n.o 5, pp. 948-956, sep. 2015, doi: 10.1093/*