Detecting Xenophobic Hate Speech in Spanish Tweets Against Venezuelan Immigrants in Ecuador Using Natural Language Processing

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Abstract. In recent reports, Ecuador and Venezuela are located as the countries with the worst social indicators, showing ethnic and racial discrimination between both countries, one possible cause is a large number of Venezuelan immigrants in Ecuador.

The present work has the goal of determining the existence of xenophobic content from a set of tweets collected around Venezuelan immigrants in Ecuador, using the diverse phases of the Knowledge Discovery in Text (KDT) methodology. Identifying xenophobia by mean of Natural Language Processing (NLP) is not an easy task; nonetheless, with the use of techniques as Synthetic Minority Oversampling (SMOTE) and Crowdsourcing it is possible to make it. The feelings classification: xenophobic, offensive and other are possible thanks to executing of three supervised classification algorithms: Logistic Regression, Support Vector Machines (SVM) and Naive Bayes.

As a result of the execution of the three algorithms, SVM algorithm obtains a better performance with an F1-score of 98%. On the other hand, of the 100% of data analysed, it is determinate that there exist a 5.76% of xenophobic sentiments, 31.23% of offensive emotions and 63% contains other feelings.

Keywords: Hate speech · Natural Language Processing · Sentiment analysis · Xenophobia · SMOTE

1 Introduction

Social networks have been a means of making the ideas and thoughts public. According to Valdez [27], this has led to an increase in hate speech by spreading messages of xenophobia, intolerance or pointing out others as a threat; such feelings are mostly directed towards vulnerable groups of people such as foreigners,

M. Botto-Tobar et al. (Eds.): ICAT 2020, CCIS 1388, pp. 312–326, 2021.
https://doi.org/10.1007/978-3-030-71503-8_24

causing them to be rejected in their environment and even with the possibility of being victims of hate crimes. This research raise the hypothesis: Are there tweets with xenophobic content towards Venezuelan immigrants in Ecuador?

This research starts with the carry out of a systematic literature review based on the phases of Barbara Kitchenham's methodology [15], which allows to determine the necessary steps to perform sentiment analysis, to few name: obtaining tweets, feature extraction, data pre-processing, application of supervised algorithms, evaluation [2,18,26] and graphic representation [1,12]. Based on this generic process, it considers applying a formal methodology like Knowledge Discovery in Text [1,14] that helps to achieve the goal of the research.

Based on systematic literature review is considered the use a set of tools, as below in detail: Python [23] and libraries of Machine Learning. Algorithms of Supervised Learning as Logistic Regression [1,24], Support Vector Machine [1,20,24] and Naive Bayes [1,21,24]. GoogleTrans library [4] is used to translate the content from Spanish to English by the Machine Translation technique, such technique allows to obtain the best results in terms of word processing, tweet collection and sentiment analysis; also highlighted fine-tuning techniques [11] that allowed to improve the performance of classification algorithms, such as the Synthetic Minority Oversampling Technique (SMOTE) [10], capable of reproducing synthetic samples of the minority classes, which allows to improve the learning of classification models.

This paper contains some sections to know: Methodology Sect. (2), where each of the phases of the methodology to feelings analysis is detailed. Later, in the Results Sect. (3), the interpretation and findings given by the implementation of the KDT methodology are presented. In the Discussion Sect. (4), the contribution of the present study is compared with the results of related studies. Finally, in the sections of Conclusions (5.1) and Future Work (5.2) the most relevant aspects of this study were raised, i.e., the experiences during its execution and what improvements can be made.

2 Methodology

The development of this study is carried out using the methodology KDT [9], whose stages are presented in Fig. 1.

In each phase, a series of additional tasks are carried out, such as the application of fine-tuning to the models, with the aim of improving the classification results of the applied algorithms. The tasks that are finally carried out are presented in Fig. 2, which are ordered according to the stages of the KDT methodology.

The process begin with the conceptualisation of the techniques, algorithms, metrics, and libraries that are used to perform the classification of xenophobic content successfully, and a series of additional tasks are performed to conclude each phase. The following is a presentation of the realisation of each of the phases of this methodology.

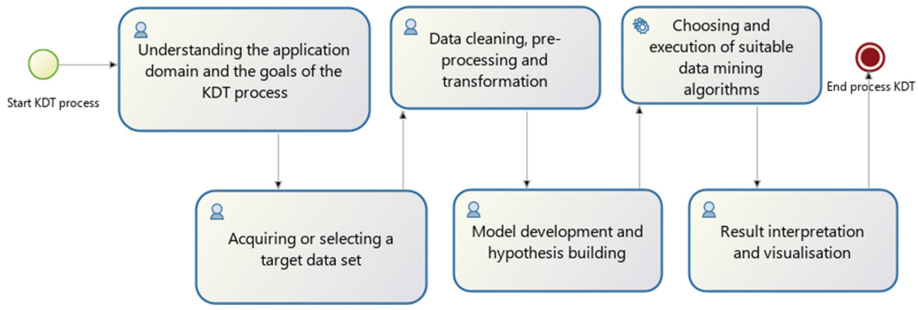

Fig. 1. Phases of the KDT methodology.

2.1 Phase 1: Understand the Application Domain and the Goals of the KDT Process

In this phase, a series of terms were defined that allowed the concepts used for the development of the methodology to be understood.

Hate Speeches. It is intended as speech to insult, offend, or intimidate a person because of some trait (such as race, religion, sexual orientation, nationality, or disability) [28].

Xenophobia. It consists of the generalised rejection of people of foreign origin, or in its case, certain groups of origin [25].

Crowdsourcing. It is the open collaboration or outsourcing of tasks, where website workers are in charge of manually sorting datasets, each observation had to be sorted by at least three people to be considered valid [6].

Machine Translation. Automatic translation has been one of the most prominent applications of artificial intelligence since its inception, there are now neural networks for automatic translation, i.e., the system can extract the patterns that allow translation from one language to another [3].

SMOTE. It is a Synthetic Minority Oversampling Technique (offered by the Imbalance-Learn library) that takes an oversampling approach to balance the original training set. This new data is created by interpolation between various minority class instances within a defined neighbourhood [10].

Fine-Tuning. The fine-tuning of a model is given by modifying its parameters or applying techniques that improve the data to be trained, to lead to a better performance of the algorithm [11].

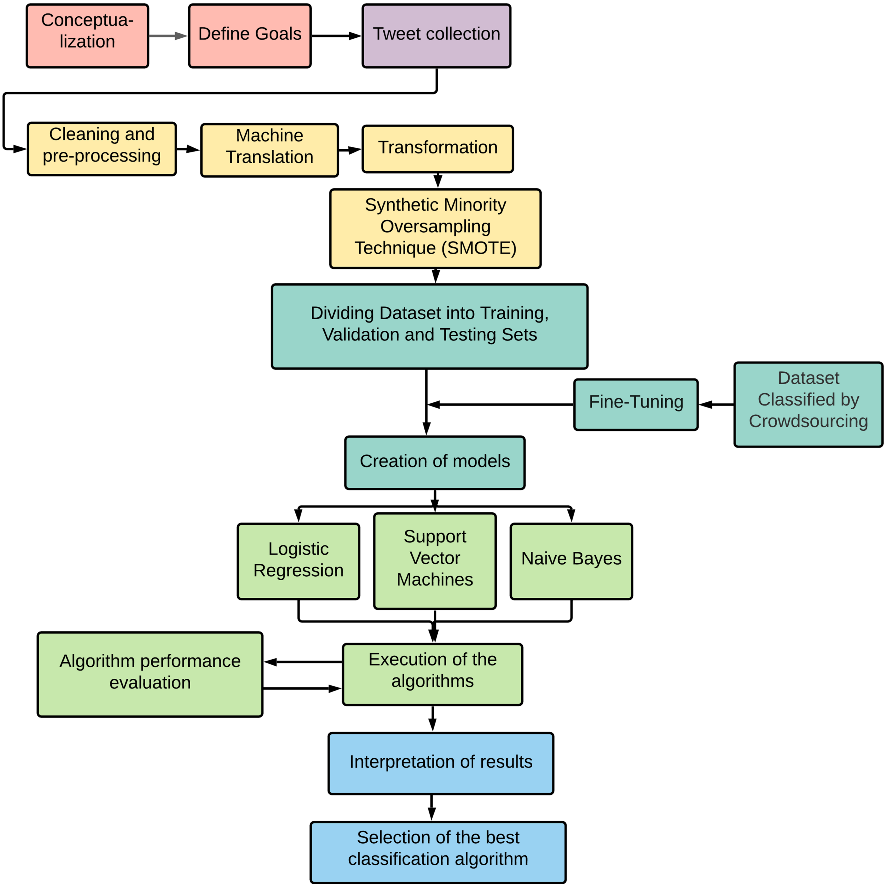

Fig. 2. KDT process that finally took place.

Accuracy. It is the proportion of the total number of correct predictions [7,17]:

$$Accuracy = \frac{\sum_{i=1}^{n} N_{ii}}{\sum_{i=1}^{n} \sum_{j=1}^{n} N_{ij}}$$

Precision. Precision is a measure of accuracy whenever a specific class has been predicted. It is defined by the formula [7,17]:

$$Precision_i = \frac{N_{ii}}{\sum_{k=1}^{n} N_{ki}}$$

Recall. It is a measure of a prediction model's ability to select instances of a particular class from a dataset, defined by the formula [7,17]:

$$Recall_i = \frac{N_{ii}}{\sum_{k=1}^{n} N_{ik}}$$

F1-Score. It is the harmonic mean of precision and recall [7,17]:

$$F1 - score_i = \frac{2 * Precision_i * Recall_i}{Precision_i + Recall_i}$$

2.2 Phase 2: Acquiring or Selecting a Target Dataset

Through the Twitter library Scraper in Python, 13,474 tweets are collected; whose search is delimited to the xenophobic content towards Venezuelan immigrants in Ecuador, applying the following keywords: Ecuador, Venezuelan, chamo/a, chamos/a, racism, out, hate, murder, xenophobia, immigrants, migrants, migration and also the library is configured to obtain results through the geolocation (Ecuador) of each tweet.

According to "Migración del Ministerio de Gobierno del Ecuador" (Migration of the Ministry of Government of Ecuador) [13], in the period from 2016 to 2019, there have been more than 300 thousand migrants of Venezuelan nationality that have stayed to live in Ecuador, for this reason, it is considered that the most feasible range for the data collection on Twitter is from January 2016 to December 2019.

Using these criteria, a dataset is collected and formed, where it is found that the texts contained irrelevant characteristics, such as their identifier, username, amount of likes, etc. Finally, only the characteristic "text" is considered relevant, since this field is sufficient to answer the research question: Are there tweets with xenophobic content towards Venezuelan immigrants in Ecuador?

2.3 Phase 3: Data Cleaning, Pre-processing and Transformation

In this phase, the cleaning, pre-processing, and transformation process are carried out to both datasets as shown in Table 1.

Table 1. Datasets used. There is the dataset that has been previously classified by crowdsourcing that was obtained from Davidson et al. study (named Dataset 1) in which he considers the classes of hate speech, offensive language or none, and that collected in the context of Venezuelan immigrants in Ecuador (Dataset 2).

Name	Context	Final size
Dataset 1	Previously classified by crowdsourcing	24,783
Dataset 2	Collected in the context of Venezuelan immigrants in Ecuador	9,888

From both datasets, the characteristics of interest are taken to carry out their cleaning and pre-processing, discarding those characters or words that do not contribute to the build of the classification model. From the Dataset 1 is taken all its 24,783 tweets and through the RegEx library, with the use of regular expressions is eliminated, unnecessary texts contained in each tweet. The regular expressions used are shown in Table 2. The same process is applicable for the Dataset 2 with its 13,474 initial tweets and later also to remove the duplicate tweets. Finally, from this last dataset, a total of 9,888 tweets is left ready to be processed in further stages.

Table 2. Use of regular expressions.

Type of text	Regular expression
User mentions	‘@[\w\-]+’
Hashtag	‘#[\w\-]+’
Links	‘http[s]?://(?:[a-zA-Z]—[0-9]—[$-_@.& +]—’ ’[!*\(\),]—(?:%[0-9a-fA-F][0-9a-fA-F]))+’
Special characters and punctuation marks	‘\W’
Excess spacing	‘\s+’

Dataset 1 is used to train the classification models, which according to Davidson et al. [6], this classification is done through crowdsourcing by CrowdFlower workers.

Dataset 1 present an imbalance in its classes, as shown in Fig. 3, in which 19,190 tweets are classified as offensive sentiments, 1,430 tweets as hate speech, and 4,163 tweets as other sentiments, which causes a bias when training the classification models, causing a lower performance during the learning of the models. For this reason, it is applied the Synthetic Minority Oversampling Technique (SMOTE), which creates new examples from existing data, i.e., using an automatic sampling strategy and with a number of k (10) neighbours, it is possible to increase the data for the minority classes. This process consist of taking a tweet at random from the minority class and from the nearest k neighbours a randomly select neighbour is chosen, and a synthetic example is created at a random point between the two examples [19].

Before applying this technique, by means of the Scikit-Learn library the texts are transformed into vectorised values to enable their processing, carried out via the TF-IDF (Term Frequency Inverse Document Frequency) model and the use of the English stop words given by the NLTK library, to discard those words that are not very relevant for the word vocabulary. After the application of the SMOTE technique, a classified dataset was obtained with all its classes balanced, i.e., the minority classes increased their observations to 19,190 each. Then Machine Translation is applied to Dataset 2 through the GoogleTrans library for the mass translation of these tweets and for their vectorisation the same TF-IDF frequency model is used to vectorise the tweets of Dataset 1, the same frequency model is used to generate the same amount of characteristics in both datasets for their later use.

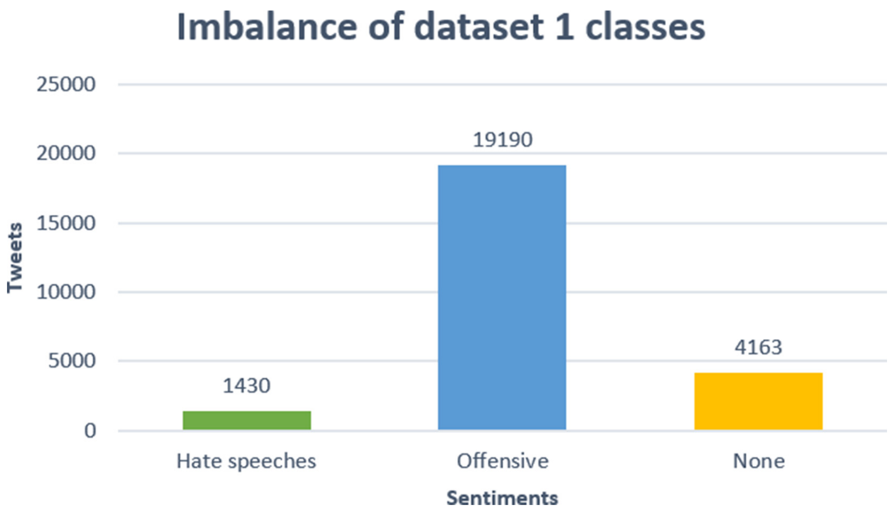

Fig. 3. Imbalance in the dataset 1 classes.

2.4 Phase 4: Model Development and Hypothesis Building

The detection of xenophobia is done in the messages that contain hate speech, the same that cover racism and hatred of foreigners, which is why, for the construction of our model as mentioned above, it is took a classified dataset that Davidson et al. [6] used to train the models, which obtained an accuracy of 91%, recall 90% and F1-score of 90%.

Before creating and applying the models for Dataset 2, it is started by creating a balanced model of Dataset 1, and then in the Discussion (4) section, we compared it with the results of this same dataset but with its initially unbalanced classes.

According to Leonardo et al. [16], it is recommended to use 80% of the data for training and 20% for testing, these datasets are created randomly through the Scikit-Learn library.

For knowing the real performance of a model before applying it, there is a very common solution, which is to use the training set to train and validate at the same time, known as cross-validation; it consists of dividing the training set in k equal parts, if k = 5 then the model is trained with the first four parts and tested with the fifth, then it is trained with the first three and the fifth and tested with the fourth, this is repeated k times, always leaving out one part for the test, then the performance in each one is averaged and thus the expected performance is obtained [5]. For the validations, it is considered to use k = 10 (number of folds), which is the number of parts into which the dataset is divided to train and evaluate the models.

Table 3 below presents the results of the cross-validation for each of the classification algorithms applied to Dataset 1.

Table 3. Cross-validation and F1-score for dataset 1

Algorithm	Cross-validation	F1-score
Logistic Regression	0.925	0.93
Support Vector Machine	0.934	0.94
Naive Bayes	0.884	0.89

The results obtained in the cross-validation in theory are the values closest to reality, which was confirmed when applying the model to a set of tests, giving values similar to those given by the cross-validation; these values are represented by the F1-scores (see Table 3).

2.5 Phase 5: Choosing and Execution of Suitable Data Mining Algorithms

For the execution of the algorithms, the models tuned in the previous phase are used to carry out the classification of Dataset 2, the update of the names of the classes of this dataset is carried out because it is created with tweets directed to Venezuelans who live in Ecuador, where the wide field of the speeches of the hate is reduced to the specific ones of rejection to the foreigners (xenophobia) and the class previously called "None" is changed for "Other" since it represents better the field of feelings that this category includes. The classification made for Dataset 2 is shown in Fig. 4.

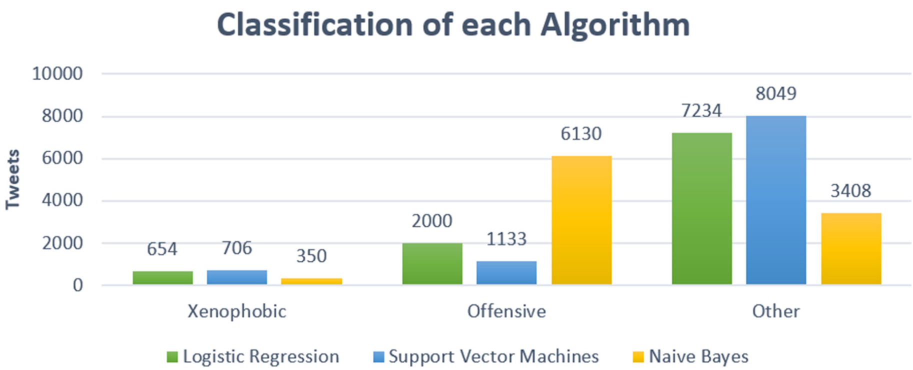

Fig. 4. Classification of dataset 2 according to each algorithm.

As can be seen in Fig. 4, through these algorithms a similar classification between each class is obtained, in contrast to the Naive Bayes algorithm that presented dissimilar results compared to the others. To create the Dataset 2 classification models with xenophobic content, the SMOTE technique is applied,

Table 4. Dataset 2 classification and the balance between its classes.

	Initial classification			SMOTE		
	Xenophobic	Offensive	Other	Xenophobic	Offensive	Other
Logistic Regression	654	2,000	7,234	7,234	7,234	7,234
Support Vector Machine	706	1,133	8,049	8,049	8,049	8,049
Naive Bayes	350	6,130	3,408	6,130	6,130	6,130

also with an automatic sampling strategy and a k = 10 (number of neighbours) in order to create new data for the minority classes (see Table 4)).

Once the datasets with their balanced classes are obtained, new models capable of classifying tweets with xenophobic content are created. These models are in a GitHub repository[1].

3 Results

3.1 Phase 6: Results Interpretation and Visualization

In Table 4 the classification results for each of the algorithms can be seen, values that vary between one or another algorithm, therefore, the overall percentage average for the three algorithms are also obtained, as presented in Fig. 5.

Once these classification results are obtained, a new model is trained for each algorithm with the balanced classes, the results of the tests carried out for these models are summarized in Fig. 6.

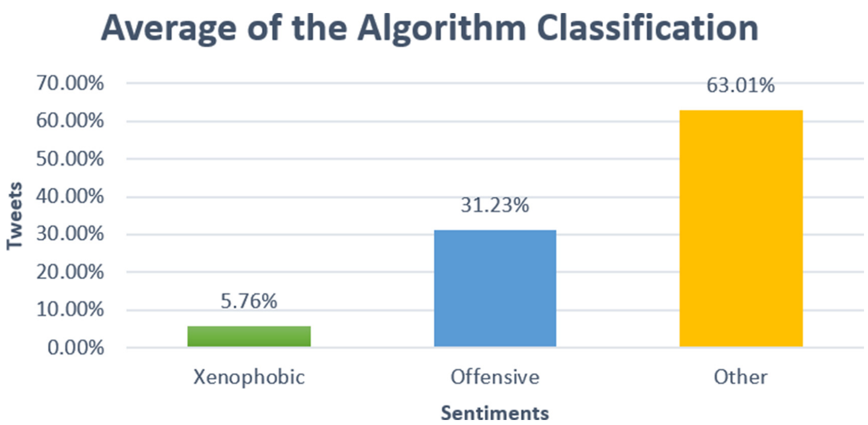

Fig. 5. Percentage average of the tweets classified, according to each sentiment.

[1] https://github.com/raulrrv/Deteccion_Xenofobia_TT/tree/master/modelo.

The final classification models are trained with their balanced classes, to obtain a better performance in each model, as can be seen in Fig. 6, the Support Vector Machines obtained the best performance with 98%, the Logistic Regression algorithm with 96%, and Naive Bayes with 89% of F1-score.

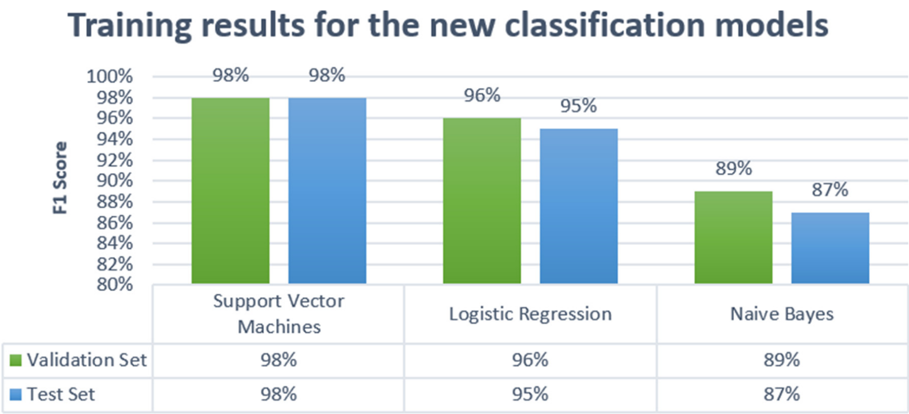

Fig. 6. Training results for the new classifying models of the xenophobic sentiment.

As a way of testing the precision with which they predict the models created, a few tweets are presented in Table 5 that are classified as xenophobic.

Table 5. Examples of tweets classified as xenophobic.

Original tweet	Machine Translation	Prediction
Venezolano no te queremos en nuestro país	Venezuelan we don't want you in our country	Xenophobic
Odio las novelas venezolanas pero aquí en Ecuador se pasan contratando actores venezolanos desconocidos, malos, gays y ridículos	I hate Venezuelan novels, but here in Ecuador they go on hiring unknown, bad, gay and ridiculous Venezuelan actors	Xenophobic
Ya de una embalalos mándalos fuera de Ecuador sidosos, ladrones, maricones de más no los queremos aquí fuera venezolanos fuera	Hurry up and get them out of Ecuador, they're too thieves, faggots, we don't want them out here, Venezuelans out	Xenophobic

Finally, with the classification already performed to the Dataset 2 that is framed with content directed towards Venezuelan immigrants in Ecuador, it is possible to answer the research question: Are there tweets with xenophobic content towards Venezuelan immigrants in Ecuador? Yes, there are tweets with xenophobic content towards Venezuelan immigrants in Ecuador, with a presence of 5.76%, which is relatively low compared to 31.23% of tweets found with offensive content towards them, also the existence in 63% of other sentiments.

4 Discussion

According to the bibliographic review, we found the study by Plaza Del Arco et al. [22] that analyzes and detects xenophobia in a set of tweets, as well as other similar works or studies, as is the case with the research of Davidson et al. [6], in which they begin by classifying a dataset with tweets in the context of hate speech, offensive language and other sentiments by means of crowdsourcing[2].

In order to create a classification model to make predictions to other data sets, this model is used to make the Dataset 2 classification, which is improved because its model had deficiencies due to an evident imbalance in its classes, this is a weak point during the training of a model, making it inefficient or low performance in the accuracy of its predictions, for this reason, in the present investigation, the number of samples is increased by creating new synthetic data of the minority classes through SMOTE, which creates new classification models for each algorithm. The results of the best precision performance by the study

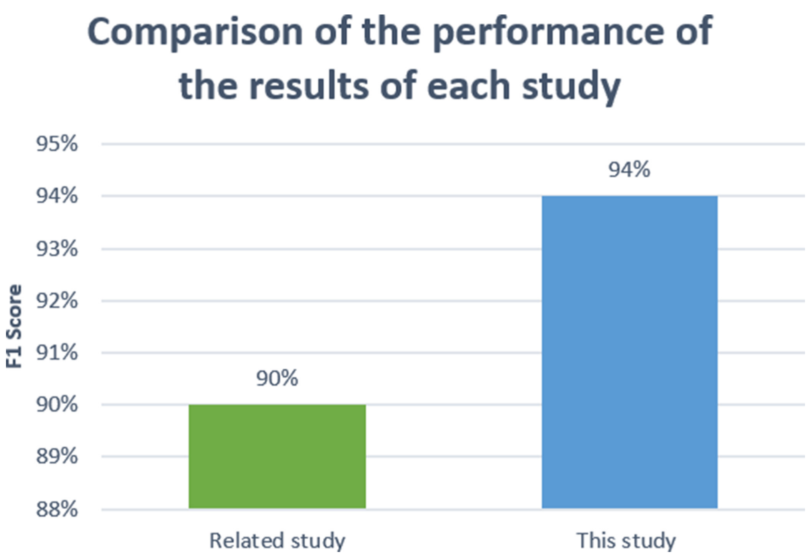

Fig. 7. Comparison of the performance of the results of the related study and the present study.

[2] https://github.com/raulrrv/Deteccion_Xenofobia_TT/blob/master/data/dataset_1_clasificado.csv.

of Davidson et al. are presented in Fig. 7, together with the results of the best performance by the algorithm of this research.

The results of the related study refer to the F1-score of the most efficient model by Davidson et al. with 90% accuracy, which is improved by the present research by balancing its classes, giving an F1-score of 94% of the best model, being the Support Vector Machine algorithm.

On the other hand, the related work of Plaza Del Arco et al. [22], in contrast to the present research detects xenophobia by creating lexicons of words that indicate hatred towards immigrants; uses lexicons to classify a tweet as xenophobic or not. The performance of its best algorithm is 73%. This low performance is possible due to the misclassification that occurs when using patterns based on word terms since a negative word in a positive context can be considered as a xenophobic tweet, marked as a false positive and leading to be misclassified.

5 Conclusions and Future Works

5.1 Conclusions

Through the application of the KDT methodology, it was determined that there is indeed xenophobic content in the social network Twitter directed to Venezuelan immigrants in Ecuador, although in a smaller proportion, since, out of the 9,888 tweets classified only 5.76% are xenophobic i.e. 570 tweets, however, this does not mean that the rest of the content is friendly since it is also found that 31.23% of the tweets published contain offensive messages towards them.

According to the literature review, it is determined that there is not enough information to detect more complex feelings such as xenophobia, i.e., the found studies of feelings analysis determine mostly only the polarity of a text (positive, negative or neutral), thru the development and fine-tuning of a classification model it is possible to detect xenophobic feelings in the set of tweets, these models have their importance for their use in similar or future studies.

Based on the performance tests of the classification algorithm models, it is concluded that a better performance is obtained when the classes of the training set have been balanced i.e. when the number of samples of the minority classes increases.

Comparing the results of each classification algorithm, it is concluded that the algorithm with the best performance results during the predictions with 94% F1-score is that of the Support Vector Machines, as well as it is also worth mentioning that this algorithm, unlike that of the Logistic Regression and the Naive Bayes, is the one that has taken the longest time to create the model, as it constantly searches the classes to find the best hyperplane that maximises the margin separation between these classes.

5.2 Future Work

To implement a software solution capable of automating the classification process of a given set of data or texts, since, through this research, a model with the highest performance algorithm (SVM) was trained to recognise texts with xenophobic content[3]. On the basis of this research, other algorithms can be applied to try and improve its results, including Google's relatively new BERT [8] system, which analyses and understands the context and subject matter of the whole sentence to be processed, allowing the generation of new results that can be compared with current research, which would also be a contribution to other research.

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