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Utilizing Sentiment Analysis to Enhance the Quality of Online Learning

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Problem Statement

- Online learning is a new subject for most students and teachers. Therefore, several things could be improved in getting the complete advantages of online learning.
- In this research, sentiment analysis techniques and machine-learning methods will be applied to a dataset containing people's reviews about online learning to derive patterns to enhance the quality of online learning.

Motivation

- COVID-19 is a Real-world problem.
- Developing The online learning sector can achieve significant improvements in various areas by knowing what people like and dislike in advance.
- The pandemic affects students and Educational Staff.
- Apply Sentiment analysis to enhance the quality of online learning by applying it to user reviews.

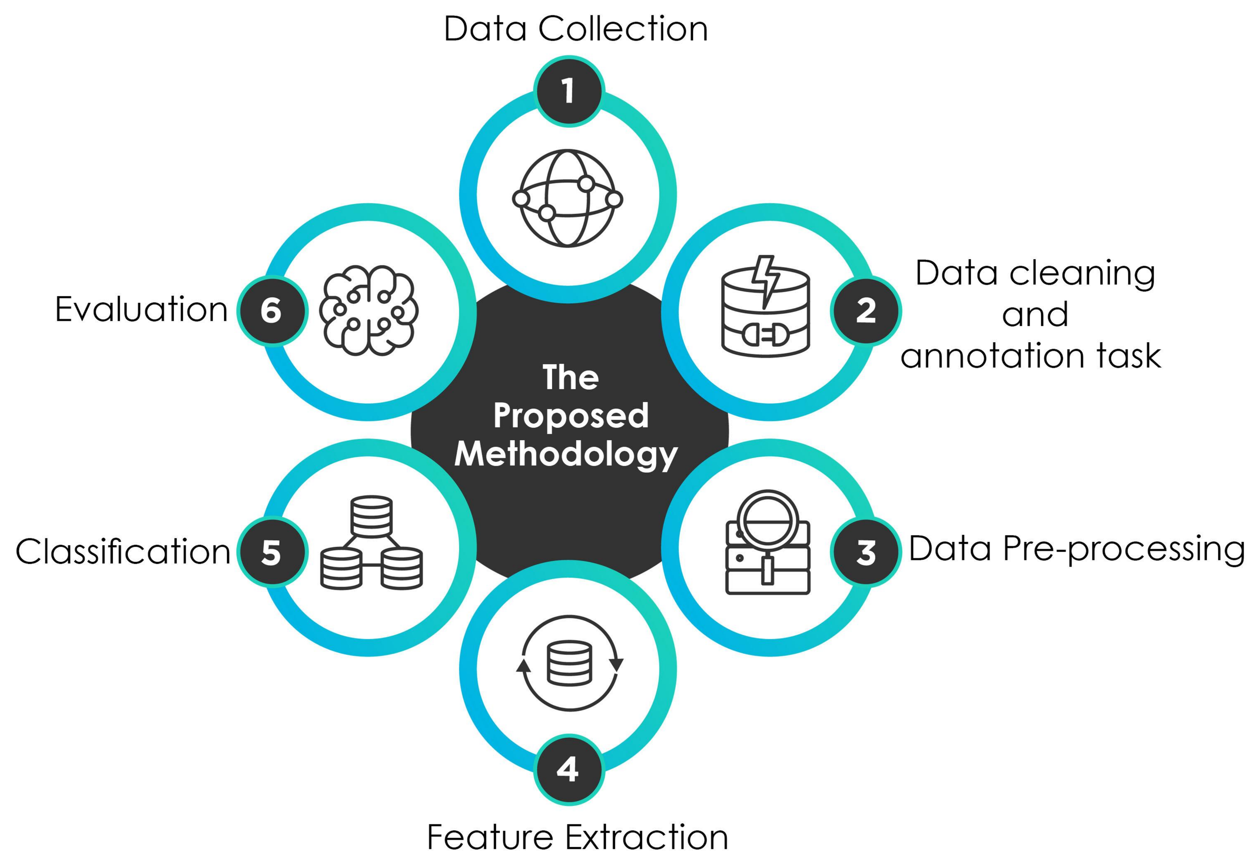
Contributions

•We constructed a dataset that contains Arabic tweets from the data set obtained from two hashtags: (منصة_مدرستي) (My School Platform) and (التعليم_عن_بعد) (Distance Learning). The dataset has been manually annotated with the help of three annotators.

•Apply Sentiment analysis to the collected data to enhance the quality of online learning.

Methodology

The methodology includes various steps used to perform Arabic SA on collected tweets. These are the major steps:

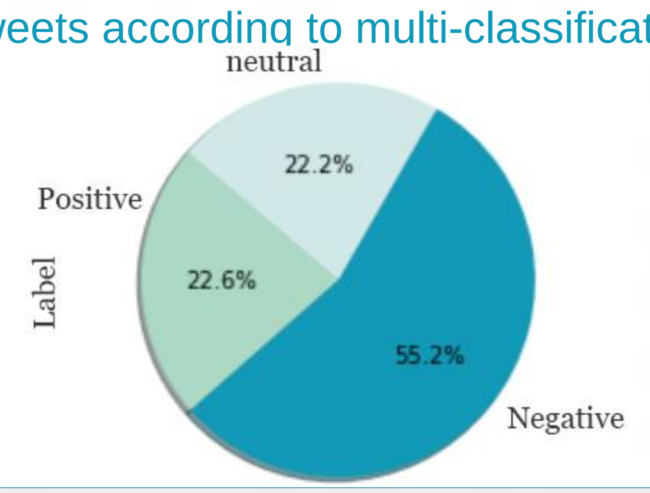


Methodology

Data set

1. The data collected in 2020–2021.
2. Data set obtained from the most common hashtags used by the educational staff, students, and teachers to express their feelings and opinions about their experience of online education and the Madrasti platform.
3. About 100,000 Arabic tweets were collected, which was reduced to 7,115 tweets After filtration.

The distribution of tweets according to multi-classification:



Experiments and Results

All the experiments are run using 10-fold cross-validation. Also, all algorithms are implemented in the scikit-learn library written in Python.

Model	Class	Precision	Recall	F1-score
SVM	Positive	**0.77 ± 0.27**	0.54 ± 0.25	0.61 ± 0.16
	Negative	0.66 ± 0.07	**0.97 ± 0.07**	**0.79 ± 0.03**
	Neutral	0.59 ± 0.20	0.06 ± 0.07	0.11 ± 0.11
RF	Positive	0.75 ± 0.29	0.54 ± 0.25	0.61 ± 0.18
	Negative	0.66 ± 0.07	**0.97 ± 0.07**	0.78 ± 0.03
	Neutral	0.58 ± 0.27	0.03 ± 0.04	0.06 ± 0.06
KNN	Positive	0.53 ± 0.18	0.52 ± 0.14	0.52 ± 0.12
	Negative	0.69 ± 0.06	0.74 ± 0.17	0.71 ± 0.09
	Neutral	0.31 ± 0.08	0.24 ± 0.08	0.27 ± 0.07

Experiments and Results

The following points can be observed :

- SVM gets the highest values for Precision among all three classes, 77%, 66%, and 59% for Positive, Negative, and Neutral, respectively.
- A similar effect is observed for recall and F1-score, where the SVM algorithm gives the highest values except for the neutral class.
- Meanwhile, KNN appeared to be the worst-performing algorithm.
- To conclude, the SVM obtained better results than other classifiers for both positive and negative classes.

Conclusion and Future Work

- Multiple ML algorithms were implemented, such as SVM, KNN, and RF. We recorded the precision, recall, and F measures for each experiment.
- We conclude that SVM works well with this kind of online learning data.
- In the future, we plan to analyze more data to make our predictions more accurate.
- We can use other efficient techniques to have balanced datasets, such as over-sampling and under-sampling techniques.
- Other models, including neural networks and deep learning, could also be employed. Furthermore, this work can be extended to other related domains.