shows the accuracy results compression between SVM and RF classifiers. SVM classifier performed 0.81, 0.70, and 0.72, while RF classifier performed 0.84, 0.80, and 0.75 classifiers for knowledge, skill, and affective objectives, respectively. RF classifier achieve higher rates than SVM classifier for all educational objectives. These results guided our decision to make the RF classifier be the chosen classifier.

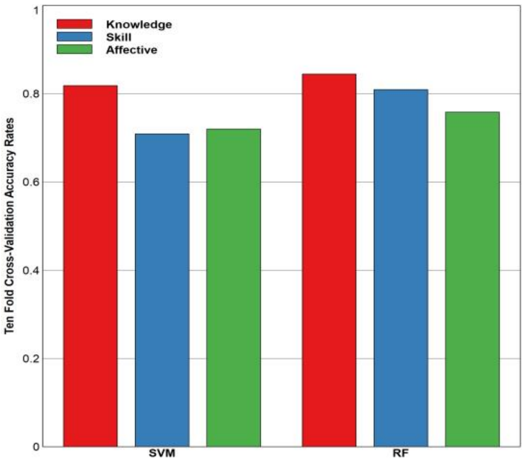

Figure 2. Classification Models Compression Accuracy Results

5.2. Different Percentage of Training Set Results

One of the important validation strategies is to evaluate the classification model in real situation, where the classifier is trained in part of the date set and being tested in the remained part. In this experiment, we trained the RF classifier into various percentage of the data from 0.1 until 0.9 and test it individually for each time.

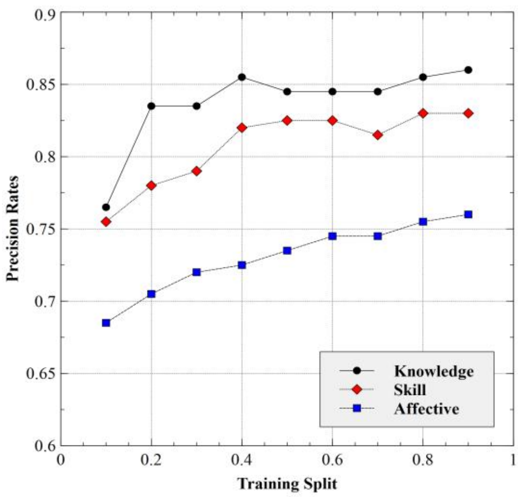

Figure 3. Precision rate results

Figure 3 presents the precision, recall, and f-score rate results for each educational objectives in different percentage of training sets. In Figure 3, the knowledge objective performed the highest precision result rates compering to the other two objectives with 0.86 in the trained split of 0.9. The affective objective performed lower starting with 0.68 in the trained split of 0.1 until 0.75 in in the trained split of 0.9.

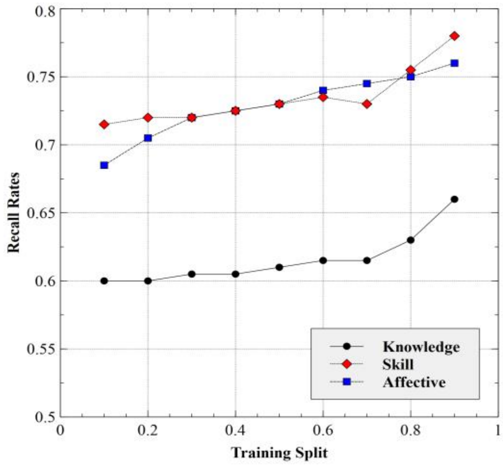

Figure 4. Recall rate results

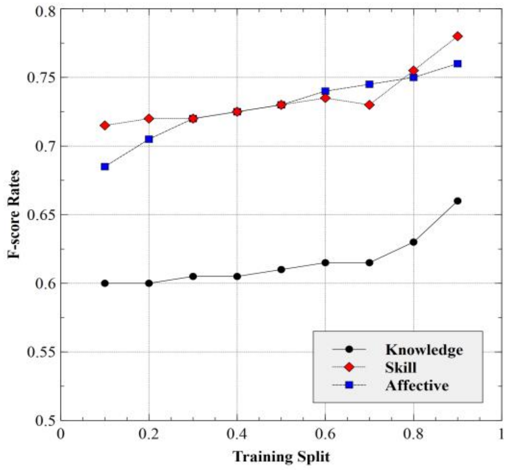

Figure 5. F-score rate results

Figures 4 and 5 show the recall and F-score performance results. Both figures generated a highly comparable plot results. The skill and affective objective performed higher than knowledge objective with about 0.76 and 0.75 in trained split of 0.9, meanwhile the knowledge started up with 0.6 in the trained split of 0.1 with little of improvement to ended up with about 0.67 in trained split of 0.9.

5.3. Different Number of Verbs

This experiment studies the impact of the number of verbs on the classification model predictions. In our work, the number of words of each educational objectives were as: knowledge (77), skill (256), and affective (295). The experiment was build based on single user tweets, which about 3135 observations and a five cross-validation in order to calculate the accuracy rates for various number of affective verbs, where it starts with 10 verbs until reaches the full collected verbs (251). Figure 4 shows the accuracy rates achieved the highest in less verbs (10) with 0.99 accuracy rates, then start to decrease as long as the number of the verbs are increased until 0.77 rate. The reason behind of these decreasing rates is the classification model can get confused with many of verbs because it generates large predictions for these verbs. A good exercise is to have considerable verbs that suited for the size of a particular data set.

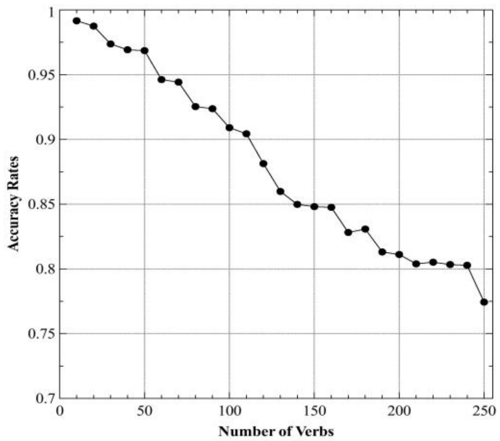

Figure 6. Accuracy Rates with Different Number of Verbs

6. Conclusion and Future Work

This paper addresses the concept and implementation of a characterization of Arabic text for the purpose of predicting and classifying the Twitter accounts based on their educational objectives such as: knowledge, skill, and effective. The data is collected from about 48 twitter Arabian educator accounts. Our purposed method started with cleaning the collected text, then used various algorithms such as: SVM and RF. We conducted several experimental results. The first experiment compares between two classification models were RT perform better than SVM classifier with above 0.75 for the all learning outcomes based on educator Arabic tweets. The second experiment used different percentage of training sets started from 0.1 until 0.9 for the RT classifier based on three classification metrics: precision, recall, and F-score rate results for each educational objectives. The precision rate results perform the best when educational objective is knowledge with 0.86 accuracy rates. Where the recall and F-score rate results perform the best when educational objective is skill with about 0.76 accuracy rates. The third experiment shows results the RF classifier performed with different number of affective verbs where it was build based on large single user tweets. The accuracy rates is decreasing as the number of verbs is increased from 0.1 until 0.77. This happens because the classifier generates large predictions for the verbs.

In future the work, we intend to collect more text data size in order to refine our results. One of the improvements could be is to use the ensemble learning which is a combination of multiple classifiers to boost the overall predictability. In terms of educational objectives and related verbs, a future study could be a comparison between the classifier results and educational experts' perspectives on tweet text classification. Knowing that data are capable of yielding direct value and are useful across all levels of the education system is critical to ensuring data quality. In fact, the extent of data use at least partly determines data quality. After all, the more useful data is to an adult educator, the more incentive there is for that adult educator to ensure that the data is produced in an accurate and timely manner. In addition, the machine learning model can provide an automated way of solving problems like classifying learning objectives. It helps beginning adult educators to classify and verify the learning objectives of their contents in twitter. Finally, a similar study could be conducted within the kingdom of Saudi Arabia standards of learning outcomes verbs.

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