6 CONCLUSION

In this work, we present a new method to improve the performance of the prominent RF classifiers for text classification using a new dynamic ensemble selection (DES) method where the competency of the trees are determined by evaluating the features used by the trees to make predictions. Contrary to popular DES approaches that apply only the competent trees to an instance, we apply all the decision trees in an RF and combine the reliable predictions for generating the prediction of the RF. Moreover, the traditional approaches evaluate the trees on a small validation set to determine competency whereas the proposed Semantics Aware Random Forest method uses the semantic explanations of the predictions to determine their reliabilities. Our method computes relevance scores between a prediction and all target classes using TFIDF weights of the words in the semantic explanations. The reliability is determined by comparing the class receiving the maximum relevance score with the predicted class. The experimental results on 30 text datasets demonstrated that (i) existing DES methods fail to improve the performance of RF for text classification, but (ii) the proposed method achieves statistically significant improvement over the traditional RF as well as existing DES methods. In future, we aim to extend the concept of reliability measure to other ensemble algorithms in order to increase their performance.

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