TABLE VI
SIGNIFICANCE TEST FOR ALGORITHM ACO-KNN WITH ALGORITHMS IG-GA AND IG-RSAR

Dataset	ACO-KNN & IG-GA (Value p)	Significance	ACO-KNN & IG-RSAR (Value p)	Significance
Nikon	0.1434	-	0.0002	+
Nokia	0.0001	+	0.0233	+
Apex	0.0087	+	0.0253	+
Canon	0.4553	-	0.0069	+
Creative	0.1158	-	0.047	+

Statistical results from the significance test (t-test) indicate that the ACO-KNN algorithm is better than the IG-RSAR & IG-GA algorithms in terms of its significance; except for Nikon, Canon, and Creative datasets. The researchers have identified three reasons behind the good performance of the proposed approach:

1) The significant difference between this work and previous studies by [4], [5] and [18] is that the approach used in this research employs a more systematic feature selection process. The feature selection method (ACO-KNN) used is capable of producing optimum feature set. Based on this approach, texts have to be preprocessed before feature selection takes place. This step is important to ensure that the feature set is optimized with only the highest quality and most important features.

2) The proposed method in this study differs from previous methods as used by [6], [7], and [10]. This study employs an interactive method in finding the relationship between features and sentiment words, whereby a principle-based approach that combined typed dependency relation with POS tagging was used. Additionally, this method is also capable of identifying relationships between features and sentiment words for up to five layers TDR (multiple layers).

3) Most of the previous studies, the study by [4], [5] for example, only took into account nouns or noun phrases in identifying features in sentences. However, an analysis on selected data sets revealed that features may consist of a noun, a verb, or even the combinations of noun-adjective or noun-verb. Additionally, sentiment words in previous studies [4] and [19] are mainly identified as adverbs, verbs or adjectives; whereas sentiment words in this study may consist of verb, adverb, noun or the combinations of adverb-adjective, noun-verb, noun-adjective or adverb-adjective-noun.

IV. CONCLUSIONS

In this paper, the researchers have proposed a hybrid algorithm between TDR Layer and POS Tags in identifying the expressions in sentiment words, and the relations between features and sentiment words in a sentence. The proposed algorithm is able to identify multiple layers of type dependency relations between features and sentiment words in a sentence due to its utilization of both TDR layers and POS tags. Additionally, the experimental evaluation has shown that the algorithm is able to outperform two baseline approaches. It is, therefore, conclusive to claim that the proposed algorithm can be used in practical settings. For prospective research, the researchers intend on further investigating, improving, and refining the algorithm for implicit feature detection and selection; implicit sentiment word detection and selection; and sentiment word orientation identification. The researchers also plan on conducting a study to investigate the use of pronoun features in customer review datasets in the future.

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