APPLICATION OF DECISION TREE-BASED SUPPORT VECTOR MACHINE IN MAPPING RICE FIELDS USING LIDAR INTENSITY AND HEIGHT METRICS

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ABSTRACT: Previous studies documented the effectiveness of LiDAR intensity and height information in land cover and land use mapping. The fusion and combined use of LiDAR and other remotely sensed data has been widely explored, too. With the scarcity of available imagery data, this study focuses on mapping rice fields from LiDAR data only using object-based method. Initially, confusion among classes was observed in doing Support Vector Machine (SVM) classification because of the presence of too many input variables, which contain irrelevant and redundant information. Accordingly, a feature selection technique was employed to assess the features and the variables derived from the selection process. In this study, five Decision Trees (DT) were constructed to evaluate the importance of 48 variables derived from nine LiDAR intensity metrics and three height layers. The input layers were filtered for SVM classification based on the results of the DT. The effectiveness of the method was assessed in three different locations. By using the method developed in this study, the overall accuracy and kappa index of agreement were increased, saving time and minimizing inputs for SVM. The DT-based feature selection for SVM enabled the reduction of variables by least 70%, while cutting the processing time shorter by a minimum of 59% reduction.

1. INTRODUCTION

With the Philippines' embarking on the Light Detection and Ranging (LiDAR) technology, the Nationwide Detailed Resources Assessment using LiDAR, also known as the Phil-LiDAR 2 Program, has been created as an offshoot program of the Disaster Risk Exposure and Assessment for Mitigation (DREAM). This three-year program, funded by the Department of Science and Technology (Blanco A. C., Tamondong, Perez, Ang, & Paringit, 2015), highlights the development of methods and algorithms that extract detailed resource features from LiDAR and secondary RS data. Extraction of various natural resources include agricultural, coastal, hydrological, forestry and renewable energy sources.

The major outputs of Phil-LiDAR 2 are detailed resources map that more or less contain land use and land cover features. These features are classified using various workflows that utilize Object-Based Image Analysis (OBIA) and Support Vector Machine (SVM) classification (Blanco A. C., et al., 2016). As the volume of the LiDAR datasets rise, these workflows have inherent limits, which are but not limited to processing time and hardware capabilities.

Hence, this research focuses on developing a methodology that aids SVM classification using Decision Tree algorithm. In particular, this study is on mapping rice fields using intensity and height metrics derived from LiDAR datasets.

1.1 Importance of Mapping

There are a number of mapping techniques widely used nowadays. One of these techniques is the LiDAR (Light Detection and Ranging) technology. It uses remote sensing to capture topographical images (point-clouds) that can be translated into data information. In the Philippines, LiDAR technology is used for mapping flood prone areas for disaster mitigation. It is also used for agricultural resources mapping, coastal mapping, hydrological resources mapping, forest mapping and renewable energy mapping (Blanco A. C., Tamondong, Perez, Ang, & Paringit, 2015).

Mapping of agricultural resources, especially in the Philippines, is very important. When it comes to food security, it is crucial to know where the rice is planted and harvested. Such information can be used for research and development and it will contribute to a better assessment of geographic variations in food supply (International Rice Research Institute, n.d.).

Since the Philippines is prone to typhoons, decision making related to this matter is vital. The extracted maps will help the government find solutions and prioritize actions to alleviate damage in the agricultural resource of the country.

Figure 1. Rice extent map of the Philippines 2000-2012 from MODIS Imagery (2015) with over all accuracy of 78.8 % (International Rice Research Institute, n.d.).

In 2009, the country’s rice yield decreased due to tropical storms “Ondoy” and “Pepeng”. It only raised 3.59 tons per hectare of rice compared to the year 2007 and 2008, which raised 3.8 and 3.77 tons per hectare of rice, respectively (International Rice Research Institute, n.d.).

The extracted maps will help the government create necessary plans to meet potential food shortages. Given that rice is the most important crop for most Asian countries, including the Philippines (Remote Sensing-Based Information and Insurance for Crops in Emerging Economies, n.d.).

1.2 Works on Land Cover Mapping

Land cover maps support a broad range of applications, such as in “forestry, natural hazards, urban climatology and agriculture” (Stefanski, Mack, & Waske, 2013). Human surveys became impractical as the need to create land cover maps with larger geographical areas increased. Therefore, land cover mapping that uses aerial and satellite images has greatly reduced the amount of resources expended in the generation of such maps (Aonpong, Kasetkasem, Rakwatin, Kumazawa, & Chanwimaluang, 2016).

In essence, a land cover map shows “the observed biophysical cover on the Earth’s surface” as per FAO definition of land cover. The level of detail of the biophysical covers present in a particular study area depends on the input images used. As far back as 2009, it was found that RADARSAT-2 data can be used to distinguish rice fields between other low vegetation classes. (Hoang, Bernier, Duchesne, & Tran, 2011) By 2011, classification accuracies of more than 90% were already achieved for main forest classes in a study conducted by Hoan et al. in mapping a tropical forest using optical and microwave data of ALOS.

A number of satellite images have become available to the public in the previous years that aided the production of land cover maps. In December, 2008, even the Landsat data became available to the public at no charge. Because of the availability of such data, image processing algorithms were applied to the available aerial and satellite data in performing classification of land cover features, such as water, forest and grassland.

Earlier remotely-sensed data had relatively low resolution, which introduced several problems in classifying land cover classes. A multi-layer approach has been proposed by Sophie et al. to address the “critical requirements of stability.” Another problem with the then available remotely-sensed data was the shadow, which has been addressed in the research conducted by Kasetkasem and Varshney in 2011.

In 2011, Zhai et al. were able to map a 68,401-square-kilometer island using Landsat data with an accuracy of 79.80%. In the same year, an accuracy of 83.93% was achieved by Liao on a national-scale land cover map. Though it seemed that the input image limits the quality of the classification of the land cover classes, accuracy of the generated land cover maps according to Aonpong, et al. is largely dependent on the algorithm used.

Image processing techniques that have been applied to remote-sensing images shifted from the conventional pixelbased approach to the object-based image analysis (OBIA). In OBIA, the adequacy of the classification methods is greatly dependent on the accuracy of the segmentation used (Stefanski, Mack, & Waske, 2013). While OBIA is the key factor in the accuracy of the land cover map created then, the adequate classification result relied on the quality of the segmentation.

As data with higher resolutions, such as LiDAR, become available, improvements were introduced. Automations in the land cover classification were made using Landsat TM/ETM+ images (Licciardi, Pratola, & Frate, 2009). Data fusion, such as in the study conducted by Barbanson et al., applied fusion to LIDAR and RADAR data at the feature level.

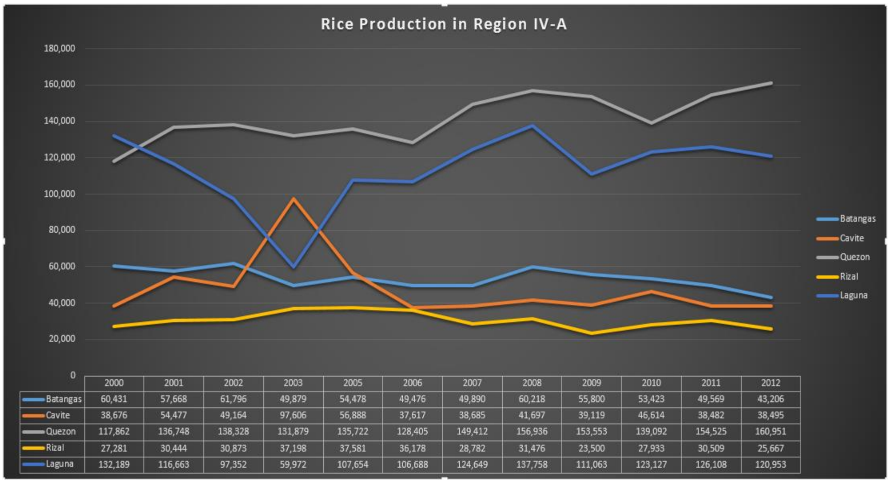
Hyperspectral images aided in the advanced classification of land cover. Integration of LiDAR and hyperspectral images improved classification accuracy. However, García-Sopoet al. in 2015 found that in order to be successful in integrating data when performing classification, it is highly needed that some aspects be addressed such as those that are "related with radiometric and geometric distortions." While data fusion generally applies to image layers, other information can be attributed to the image layers to improve the classification. Other details, such as crop rotation information can be fused with multi-temporal high-resolution optical images to improve the results of the classification (Osman, Inglada, Dejoux, Hagolle, & Dedieu, 2012). A very high resolution IKONOS-2 was used by Gil and Abadi in 2015 and it was found that this image has been accurately classified especially by using k-Nearest Neighbor and Maximum Likelihood Classifications.

In 2013, a robust methodology was made that can even attain accuracies of more than 90% (Berger, Voltersen, Hese, Walde, & Schmullius, 2013) by fusing LiDAR and HSR multi-spectral data, hence, a detailed urban land cover map has already been achieved in that year. By using LiDAR data alone and working on height and intensity data, user and producer accuracies that range from 86.8% to 93.6% have already been achievable in 2013 (Zhou, 2013).

A new land cover mapping technique was introduced by combining the strengths of the Random Forest Algorithm and the Level Set Method (Aonpong, Kasetkasem, Rakwatin, Kumazawa, & Chanwimaluang, 2016). Superresolution mapping is currently being applied on land cover mapping that is able to produce fine spatial resolution out of a coarse-spatial-resolution image (Ling, Foody, Ge, Li, & Du, 2016).Recent improvements in land cover mapping are focused on developing algorithms and on increasing the resolution of the land cover map, along with the accuracy.

1.3 Rice Production in Region IV-A

According to the Department of Agriculture-Region IV-A, the production of rice in the region increased by 7,775 metric tons from 391,418 metric tons in 2007 to 399,193 metric tons in 2011. But in addition, the yield per hectare declined from 3.74 metric tons in 2007 to 3.50 metric tons in 2011 due to conversion of rice fields to commercial and residential area (Department of Agriculture, n.d.).



	2000	2001	2002	2003	2005	2006	2007	2008	2009	2010	2011	2012
Batangas	60,431	57,668	61,796	49,879	54,478	49,476	49,890	60,218	55,800	53,423	49,569	43,206
Cavite	38,676	54,477	49,164	97,606	56,888	37,617	38,685	41,697	39,119	46,614	38,482	38,495
Quezon	117,862	136,748	138,328	131,879	135,722	128,405	149,412	156,936	153,553	139,092	154,525	160,951
Rizal	27,281	30,444	30,873	37,198	37,581	36,178	28,782	31,476	23,500	27,933	30,509	25,667
Laguna	132,189	116,663	97,352	59,972	107,654	106,688	124,649	137,758	111,063	123,127	126,108	120,953

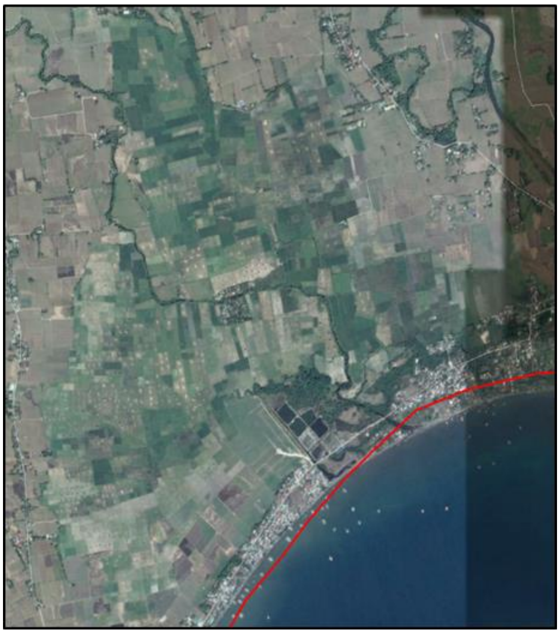
Figure 2. Rice production in Region IV-A from year 2000 to 2012 (Philippine Statistics Authority, 2016).

The harvested rice was classified into two - irrigated rice (during dry season) and rainfed rice (during wet season). The production for irrigated rice from the region was increased by 5,744 metric tons from an output of 314,735 metric tons in 2007 to 320,479 metric tons in 2011. The rainfed rice in the region increased by 2,031 metric tons from an output of 76,683 in 2007 to 78,714 metric tons in 2011 (Department of Agriculture, n.d.).

2. METHODOLOGY

2.1 Study Area and Materials

The study covers the rice field area found in Maragondon, Cavite (14°14'23.56"N, 120°44'11.77"E), Calatagan, Batangas (13°52'43.91"N, 120°38'59.58"E) and Balayan, Batangas (13°57'4.90"N, 120°42'55.26"E). Combining all extracted rice from LiDAR, the data was accumulated to 455 hectares wherein Balayan, Batangas had the largest area calculated at 324 hectares of rice fields.



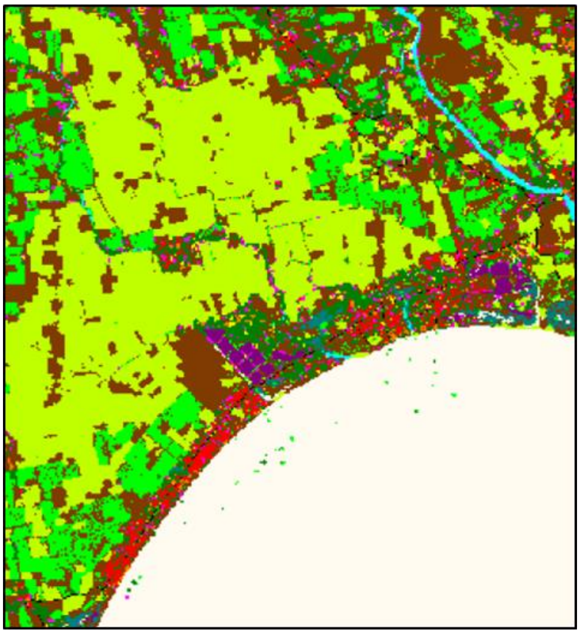


Figure 3. Satelite imagery on Balayan, Batangas shown in Google Earth Pro (left) and land use land cover (LULC) map extracted using LiDAR data.

The LiDAR data was sourced from the Disaster Risk and Exposure Assessment for Mitigation (DREAM^{TM}). From the LiDAR point clouds, intensity metrics and height metrics were derived using LAStools. The images used were the derived intensity images (all) with three height metrics (Slope, DSM and nDSM). Since the work by Carranza & Blanco (2015) used nDSM and five focal statistics from uncalibrated LiDAR intensity, we added two layers as an additional representation for height variability of rice versus other land cover, as well as four focal statistics on intensity. Statistics were computed on a per object basis, including mean, standard deviation, mode and 50th quantile. In total, 48 variables were available as input for the training phase of both Decision Tree and SVM.

Table 1. List of LiDAR derivatives.

Acronym	Meaning
INT AVG	Average intensity based on LiDAR points
INT KUR	Kurtosis of intensity based on LiDAR points
INT MAX	Maximum of intensity based on LiDAR points
INT MIN	Minimum value of intensity based on LiDAR points
INT P01	1st Percentile of intensity based on LiDAR points
INT P99	99th Percentile of intensity based on LiDAR points
INT QAV	Quadratic average of intensity based on LiDAR points
INT SKE	Skewness of intensity based on LiDAR points
INT STD	Standard deviation of intensity based on LiDAR points
DSM	Digital Surface Model
nDSM	Normalized Digital Surface Model
SLOPE	Computed gradient of the DSM raster

2.2 Feature Selection

Even with the use of LiDAR derivatives and orthophoto for SVM classification, confusion among classes were reported by Phil-LiDAR 2 partner institutions, testing various classifiers in different locations (David & Ballado, 2015a; Jalbuena, et al., 2015; Pada, et al., 2015) With the unavailability of orthophoto for many LiDAR flight missions, classification can be even more challenging, resulting to slight decrease in accuracy (David & Ballado, 2015b).

Classifiers can perform poorly because of the presence of redundant and irrelevant data.

Relying solely on LiDAR derivatives for LULC mapping, many variables (e.g. 60 for this case) can serve as input for SVM training; in which unknowns are the redundant and irrelevant variables. Hence, a feature selection technique is necessary for this problem. Generally, there are three goals for implementing a feature selection technique: (1) to improve prediction performance of the predictor; (2) to provide faster and more cost-effective predictors; and (3) to provide better understanding of underlying process that generated the data (Guyon & Elisseeff, 2003).

Although SVM performs well, a major drawback is its computational cost, particularly occurring on the training phase (Cristianini & Shawe-Taylor, 2000; Chang, et al., 2010). This happens because training the classifier requires solving a quadratic programming problem (QPP), which is a computationally expensive task (Cervantes, Farid García Lamonta, Mazahua, & Ruíz, 2015). Cervantes et al. (2015) further noted that solving the QPP becomes impractical when the data sets are huge because the amount of time and memory invested is between $O(n^2)$ and $O(n^3)$.

Recently, studies are focusing on various data reduction techniques for SVM classification. Reduction techniques prior to SVM classification have been tested by Georgescu, et al. (2010), including Principal Component Analysis, Partial Least Squares, Structurally Random Matrices and Orthogonal Matching Pursuit.

Decision Tree, a machine learning algorithm widely used in data mining, has been a tool for data reduction. DT is a binary tree wherein a series of decisions are made to segment the data into homogeneous subgroups (eCognition, 2014). The decision tree is built by undergoing a recursive process; sorting data from a node, where a test is made based on an attribute, branching to another node, where another test is made, until it reaches a final classification at the leaf node (Mitchell, 1997).

A novel algorithm was developed by López-Chau, et al. (2012) to select the most important sample from training data by guiding the sample selection giving more chance to be selected to those examples that are on the boundaries of clusters discovered by a decision tree. Although the size of training data was reduced, there was a slight decrease in the accuracy of the classifier; but they claimed that it works well for large datasets.

More recently, Cervantes, et al. (2015) improved their previous work by applying a data filter based on a decision tree that scans the entire data and obtains a small subset of data points. They also noted that the proposed algorithm works very fast even with large data sets and that it outperforms the current state of the art SVM implementations without substantial reduction of accuracy.

The built decision tree is not only used for prediction, but also for further data analyses. An important property of the constructed decision tree is its ability to compute the importance value (relative decisive power or information gain) for each feature (Mitchell, 1997; OpenCV). This can be performed in eCognition by querying the attributes of the trained DT using Query operation.

Aside from its applications in remote sensing, DT has been a popular choice as a pre-processing step for SVM classification, as discussed above. For this study, five minimum number samples per node was arbitrarily chosen for all the decision trees. Furthermore, we applied a five-fold cross validation in order to address the issue of having either too few splits (poor predictive accuracy) or too many splits (complex tree).

In a cross-validation procedure, the DT is computed from the learning samples and its predictive accuracy is tested by test samples. A poor cross-validation results when the costs for the test sample exceed the costs for the learning sample; thus, a different sized tree might cross-validate better (eCognition, 2014).

For this particular purpose, we constructed five decision trees with the following set-ups: (1) Intensity metrics, (2) Intensity metrics + DSM, (3) Intensity metrics + Slope, (4) Intensity metrics + nDSM, and (5) Intensity metrics + DSM + Slope + nDSM. For SVM classification, three set-ups were made: (1) SVM with all intensity and height metrics, SVM_{ALL}, (2) SVM with features taken from the last trial of DT, SVMDT1, and (3) SVM with features whose importance are 10% and above based on the five DTs, SVM_{DT2}.

3. RESULTS AND DISCUSSION

Examining the tables of importance generated from the five decision trees, we can say that the combination of LiDAR intensity and height is effective in mapping dominant land cover classes. LiDAR intensity images dominated the important variables for all the set-ups. This can be attributed to that fact the rice fields, because of wetness, have lower intensity values, while bare/fallow, grassland and vegetables have higher intensity values.

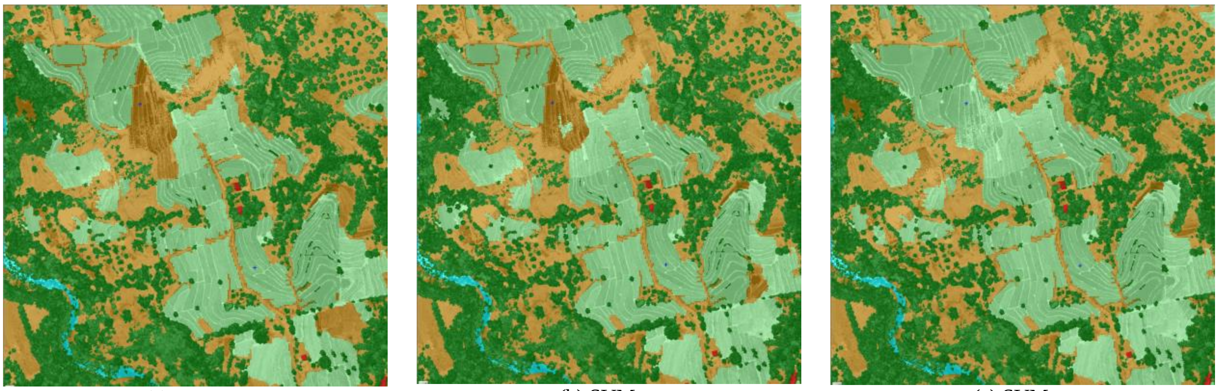
It is worth mentioning, too, that LiDAR height information improved the accuracy and visual appeal of the results. Because rice and vegetable fields are found on the flat surfaces, their DSM values are also lower compared with bare/fallow from sugarcane fields. Hence, DSM topped the list on the table of importance for Balayan (Table 3) and Calatagan (Table 4).

Based on the table of importance, we note that the use of additional variables such as quantile and mode can improve the classification, aside from the commonly used mean and standard deviation.

The accuracy assessment for SVM trials are shown on Table 2. Clearly, the trials with DT-based SVM outperforms SVM with all input variables in terms of overall accuracy (OA) and kappa index of agreement (KIA). Both OA and KIA slightly increased by using SVM_{DT2} since important variables determined from previous trials were included as input for training. The Decision Tree used as a feature selection tool prior to SVM classification enabled the reduction of input variables with an average of 83%, while also reducing the processing time by an average of 76%.

Table 2. Summary of results.

	SVM Training & Classification Time (seconds)	**Number of Features Used in Training**	**Overall Accuracy**	**Kappa Index of Agreement**	**Reduction of Time**	**Reduction of Features**
Calatagan, Batangas						
SVM_{ALL}	843.453	48	0.8417	0.7245	---	---
SVM_{DT1}	186.68	10	0.8588	0.755	77.87%	79.17%
SVM_{DT2}	180.281	10	0.9025	0.8292	78.63%	79.17%
Balayan, Batangas						
SVM_{ALL}	1182.735	48	0.8588	0.6324	---	---
SVM_{DT1}	320.109	8	0.8738	0.6911	72.93%	83.33%
SVM_{DT2}	484.109	13	0.8998	0.7339	59.07%	72.92%
Maragondon, Cavite						
SVM_{ALL}	200.625	48	0.8797	0.7318	---	---
SVM_{DT1}	35.157	3	0.9498	0.8864	82.73%	93.75%
SVM_{DT2}	30.109	5	0.9508	0.8905	85%	89.58%



(a) SVM_{ALL} (b) SVM_{DT1} (c) SVM_{DT2}

Figure 4. Comparison of outputs in rice field extraction for Maragondon, Cavite.

Table 3. Table of importance from DT set-up 5 for Balayan.

Feature	Importance
quantile[50](DSM)	0.238897481
mode[Minimum](INT_P99)	0.175142065
quantile[50](INT_AVG)	0.17014375
Mean SLOPE	0.091130694
Standard deviation NDSM	0.091036858
quantile[50](NDSM)	0.089277064
Mean NDSM	0.072209901
Mean INT_SKE	0.072162187

Table 4. Table of importance from DT set-up 5 for Calatagan.

Feature	Importance
quantile[50](DSM)	0.305098842
quantile[50](INT_STD)	0.129942575
mode[Minimum](INT_MAX)	0.125614197
quantile[50](INT_MAX)	0.114001578
Standard deviation DSM	0.105589985
quantile[50](NDSM)	0.066085711
Standard deviation INT_AVG	0.048347663
Standard deviation INT_MAX	0.043633902
quantile[50](INT_AVG)	0.041946173
quantile[50](INT_MIN)	0.019739374

4. CONCLUSION

The Decision Tree, which can generate a table of importance, forms the basis of evaluation for features that we think are helpful in the SVM classification. Moreover, the use of DT as a feature selection tool enables the assessment of each layers and the statistics derived from them. From the trials, we found that LiDAR intensity layers, alongside the chosen height layers, can enable mapping of rice as an alternative to other remotely sensed optical imagery.

The methodology introduces an effective and efficient feature selection technique prior to SVM classification. In fact, the method enabled the reduction of input variables with an average of 83%, while also reducing the processing time by an average of 76%. It exhibits effectiveness in the sense that the classifier produced better generalization as it reduced misclassification indicated by the increase in overall accuracy and kappa coefficient.

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