MEKATRONIKA
e-ISSN: 2637-0883
VOL. 2, ISSUE 1, 23 – 27
DOI: https://doi.org/10.15282/mekatronika.v2i1.6720

ORIGINAL ARTICLE

Pallet-level Classification Using Principal Component Analysis in Ensemble Learning Model

Choong Chun Sern[1,*], Ahmad Fakhri Ab. Nasir[1], Muhammad Aizzat Zakaria[1], Anwar P. P. Abdul Majeed[1], and Mohd Azraai Mohd Razman[1]

[1] Innovative Manufacturing, Mechatronics and Sports Laboratory, Faculty of Manufacturing and Mechatronics Engineering Technology, Universiti Malaysia Pahang, 26600 Pahang, Malaysia.

ABSTRACT – In this paper, we present a machine learning pipeline to solve a multiclass classification of radio frequency identification (RFID) signal strength. The goal is to identify ten pallet levels using nine statistical features derived from RFID signals and four various ensemble learning classification models. The efficacy of the models was evaluated by considering features that were dimensionally reduced via Principal Component Analysis (PCA) and original features. It was shown that the PCA reduced features could provide a better classification accuracy of the pallet levels in comparison to the selection of all features via Extra Tree and Random Forest models.

ARTICLE HISTORY
Received: 13th May 2020
Revised: 24th May 2020
Accepted: 5th June 2020

KEYWORDS
Pallet-level
RFID
Ensemble Learning
Features Selection
RSSI

INTRODUCTION

Object detection is one of the essential concerns in computer vision and radio frequency identification (RFID); it is the fundamental role of performing robot navigation and automated visual inspection control in industrial applications [1]. In certain instances, the object that is required to be identified based on the received signal strength indicator (RSSI) features is derived from the RFID tags[2], [3]. However, in industrial applications, object detection in a confined space or different levels is a challenge, and limited literature has addressed this issue in this emerging field [2]–[6].

Several studies have revealed that the use of Principal Component Analysis (PCA) is likely to yield a better classification accuracy compared to the original high dimensional feature space [7], [8]. Nonetheless, it is worth noting that it is still dependent on the choice of classifiers and feature combinations [9]. It was shown in [10] that PCA could provide a better R&D classification of the Korean ICT industries. A similar observation could be seen in the identification of retail customer behaviour [11].

Ensemble learning has been demonstrated to provide exceptional classifying of RFID tags against non-ensemble based classifiers. [12]. A different study on the efficacy of ensemble learning has also been shown to identify indoors well based on RFID signals [13]. Its practical application has also been reported in [14] to track passive RFID tags on clothes. However, it is noteworthy to mention that the recognition of significant associated statistical features is non-trivial to achieve better accuracy as well as to reduce computational expense.

This research work aims to identify significant features that are imperative for the classifying of pallet-level between the pallet boxes. This research is an extension of an earlier work reported on improving the classification performance of the pallets based on RFID signals through the evaluation of different classifiers [15]. As the RSSI values obtained from the RFID reader is regarded as time-domain based, statistical features are extracted [16]. In this study, PCA is employed to identify the significant features of the assigned class. Besides, the efficacy of different ensemble learning models, namely random forest (RF), extra tree (ET), bagging, and gradient boosting (GB), is investigated towards its ability in classifying the RSSI values from the pallet. It is hypothesised that removing unwanted, irrelevant and redundant attributes could provide a better classification of the pallet levels.

MATERIAL AND METHODS

The detailed experimental setup of the present study, i.e., the stacking of the pallet boxes and the location of the RFID reader and tags, are described in [15]. This section will elaborate extensively on the characteristics of the imbalanced RFID-tagged experimental data, feature correlation analysis, and the proposed classification model.

Received Signal Strength Indicator from RFID Tags inside the Stacked Pallet Boxes

Previous studies documented in [12], [15] presents a comprehensive set of experimental data collection of ~4,800 data instances (80 percent of the total data) used for classifier training with 5-fold cross validation and approximately

*CORRESPONDING AUTHOR | Choong ChunSern | ✉ cs_choong@hotmail.com

1,200 data instances (20 percent of the total data) that were set aside for prospective or performed validation studies, i.e. independent classifier testing. Therefore, we applied the same ratio of data splitting in the trained and test set for this study because the classification accuracy can achieve reasonable results.

Definition of balanced RFID-tagged Experimental Data

A total of 8,264 instances are obtained from the RSSI value from a sampling rate of 10 Hz of the RFID reader [15]. Nine statistical time-domain features were extracted: maximum, minimum, mode, mean, median, variance, range, kurtosis, and skewness. Table 1 lists the RSSI values captured for each level, where level 1 is located near the floor. It could be noticed that the discrepancies between the levels are not apparent, suggesting the level of difficulty in distinguishing the levels.

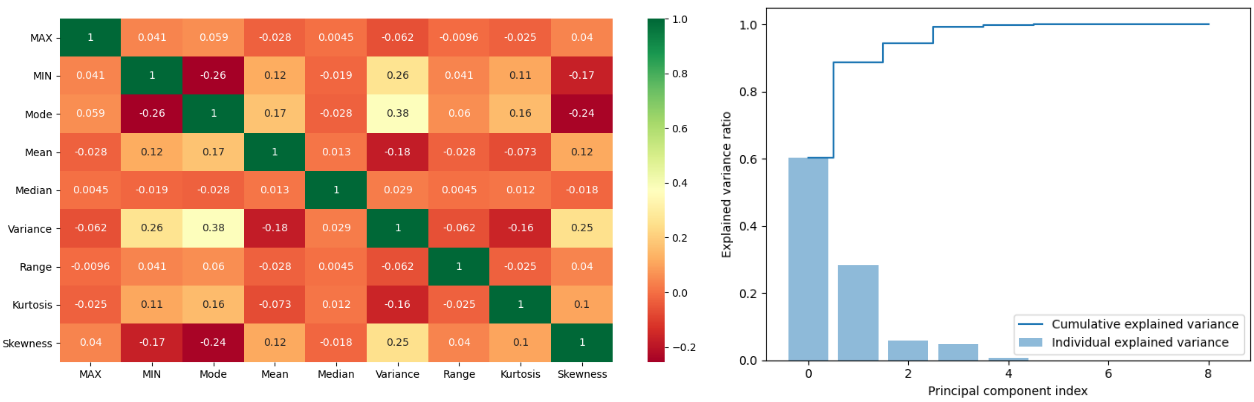
Table 1. RSSI values for each level.

Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8	Level 9	Level 10	Total
811	832	834	833	833	835	833	810	833	810	8264

Principal Component Analysis for Dimensionality Reduction and Feature Correlation Analysis

The correlation matrix between the nine extracted features is depicted in Fig. 1(a). It could be seen that some features have a strong correlation with one and another, whilst others are not. This somewhat suggests that there are features that would essentially act as a form of noise and are redundant. Through dimensional reduction technique, i.e. PCA, the insignificant features could be removed and provide a better classification of the level of the pallets.

Fig. 1(b) indicates the cumulative explained variance by each principal component (number of transformed features). It could be seen that three components could provide a cumulative explained variance of greater than 90% [17]. As a result, three (3) significant features will be selected and be compared with the unreduced high dimensional features.



(a) (b)

Figure 1. Analysis in PCA (a) Heatmap of the original statistical feature (b) Explained variance using PCA.

Hyperparameter Tuning of the Ensemble Learning Algorithms

In this study, the implementation of four various types of ensemble learning classification models, namely random forest, extra tree, bagging and gradient boosting, will be used to investigate the significance of the features selected. The number of trees hyperparameter for the random forest, extra tree and gradient boosting is set to 100. Whereas for bagging the number of trees is set to 10, whilst the rest of the hyperparameters are kept at their default values. The Gini index is used as the criteria for calculating information gain for the random forest and different tree classifiers.

The classification performance of the selection of classifiers and its associated features is evaluated via the confusion matrices as well as the classification accuracy. All experiments are performed were run on the Python programming language on a 64-bit Windows PC equipped with a single 2.5 GHz processor, Intel i7-4710HQ and 7.89 GB memory. The feature extraction tool using Microsoft Visual Studio development environment as detailed in [18]–[20] with the developed feature extraction framework. Scikit-learn libraries were used for the development of ensemble models. The overall methodology is shown in Fig. 2, beginning from the extraction of the features from the RSSI to the selection of features followed by the classification.

Figure 2. Diagram overview of the three essential stages of the data analysis process.

EXPERIMENTAL RESULTS

Classification Performance by considering Original Statistical Features

The classification performance in the balanced sampled setting for all the ten levels is shown in Fig. 3 using all nine of the statistical features extracted from the RSSI using four different ensemble learning classifiers. The classification accuracy is influenced by the misclassification elements in their respective confusion matrices, which are noticeable across all classifiers at level 2 and level 3 (illustrated by the darker shades).

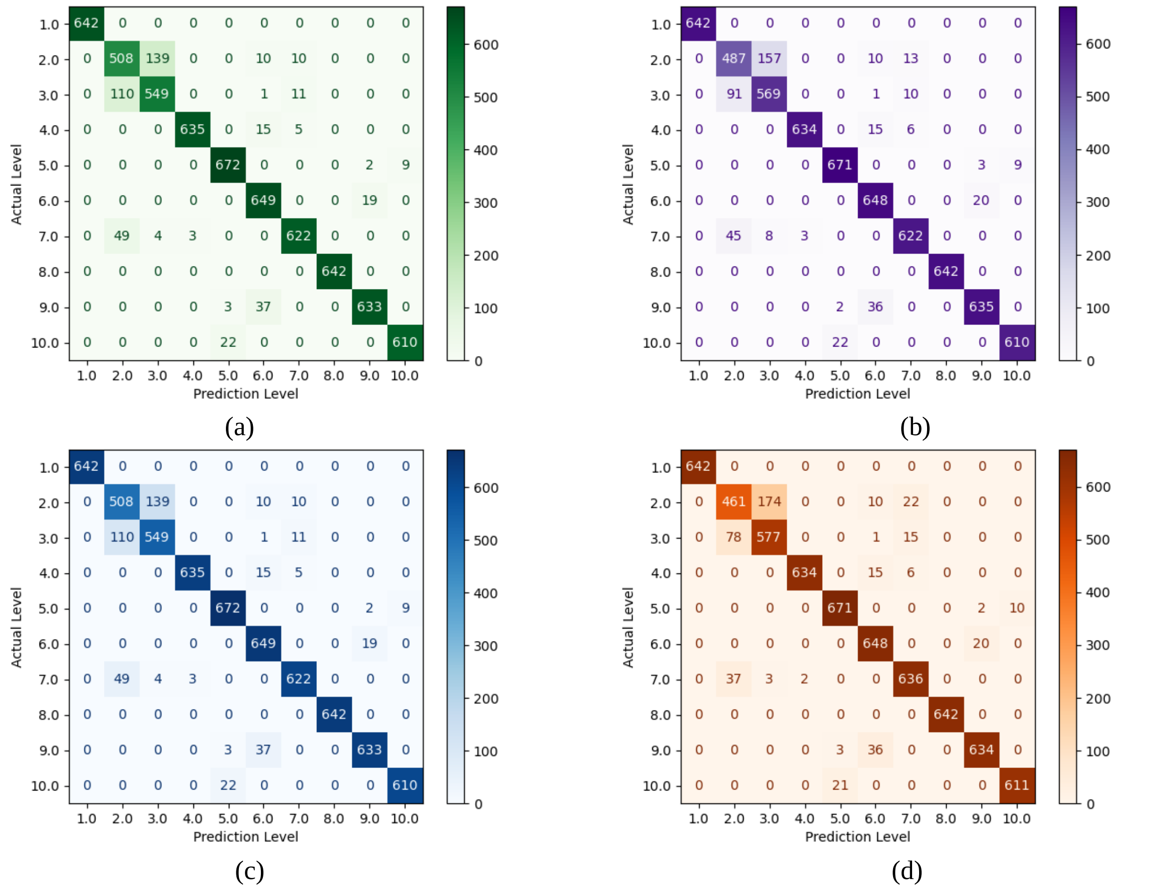


Figure 3. Confusion matrix of the original 9- statistical extracted features with different classifiers. (a) Random forest. (b) Bagging. (c) Extra tree. (d) Gradient boosting.

Classification Performance by considering Reduced Statistical Features identified via PCA

The use of explained variance in PCA is a well-established approach for selecting significant features (three). It could be seen that by considering only three significant features, the performance of the classifiers was not reduced. Moreover, it is also apparent that the misclassification also occurs at levels 2 and 3, which is akin to utilising all features. This region's misclassification could be attributed to the weak signal strength by the tags (inherent manufacturing defect) [21]. This observation is non-trivial as it suggests that by employing three significant features, a reduced computational expense could be attained. It is interesting to note that for all the four classifiers evaluated, the true positive values are higher than the findings reported in [2], [22], [23].

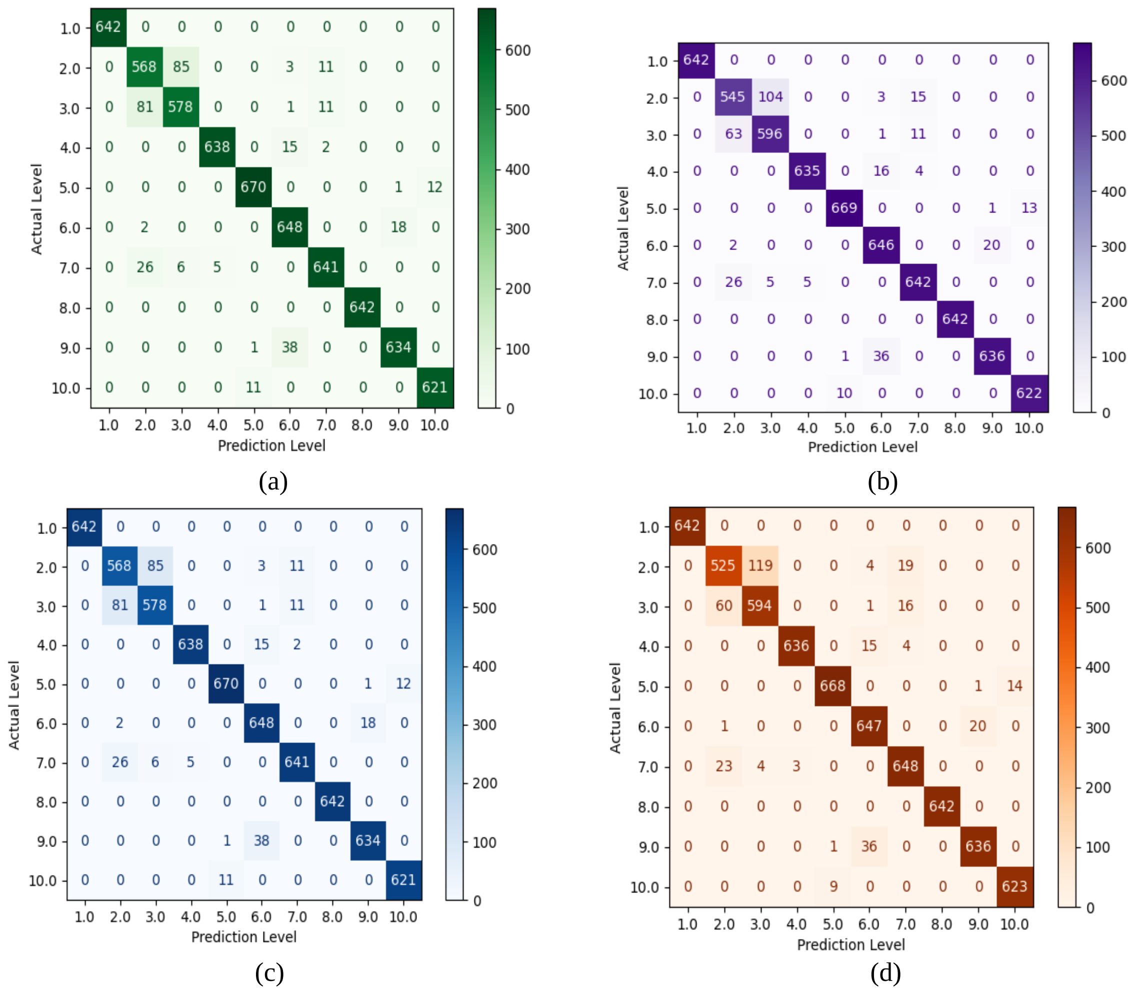


Figure 4. Confusion matrix of the reduced 3-dimensional statistical feature with different classifiers. (a) Random forest. (b) Bagging. (c) Extra tree. (d) Gradient boosting.

Classification Performance in the High Dimensional Statistical Feature and Reduced Statistical Feature

Fig. 5 depicts the classification performance of the evaluated models by considering the different feature sets, i.e., significant against all. The mean and standard deviation of the classification accuracy (CA) drawn by each classifier suggests the robustness of the models developed. It could be seen that an improved CA can be observed across all evaluated classifiers by considering the features selected via PCA. The dimensionality reduction enhances efficiency in all the cases of classifiers when compared with the original statistical feature. The best CA is achieved by the random forest (95.02%) and the extra tree (95.02%) models, followed by the bagging classifier (94.92%) and gradient boosting (94.71%) for the reduced feature set. The classification accuracy in the original statistical feature is slightly lower at 93.21%, 93.21%, 93.16% and 93.11% for RF, ET, Bagging and GB, respectively.

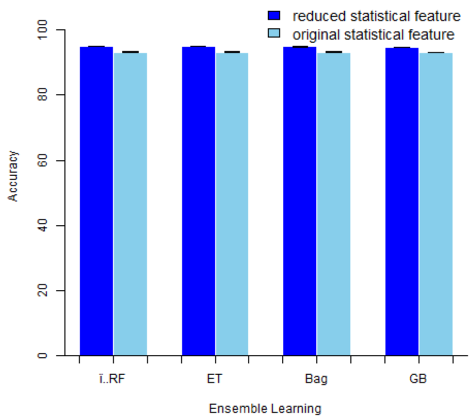


Figure 5. Comparison of classification distributions of accuracy derived from different types of ensemble learning in the original features and reduced features.

CONCLUSION

Pallet-level classification is an important challenge for logistic services. However, due to the high complexity and fluctuation of the RSSI, the typical statistical features must be extracted. Subsequently, the identification of the features could be performed, in which this study exploits the use of PCA. Different ensemble learning models were used to appraise the feature sets. It was shown from the study that the PCA reduced features could provide a better CA against the original feature set. The present study's findings are non-trivial, especially for real-time identification of the pallet levels, as reduced computational expense could be achieved through the reduced features. It is worth noting that this analysis can be further extended by investigating the effect of hyperparameter optimisation or tuning towards the CA of the pallet levels.

REFERENCES

[1] L. Bolotnyy, S. Krize, and G. Robins, “The practicality of multi-tag RFID systems*,” in *Proceedings of the 1st International Workshop on RFID Technology - Concepts, Applications, Challenges IWRT 2007; In Conjunction with ICEIS 2007*, 2007, pp. 100–113.

[2] M. Jo, S. H. Cha, H. Choo, and H. H. Chen, “Prediction of RFID tag detection for a stationary carton box,” in *Proceedings of the 3rd International Conference on Sensing Technology, ICST 2008*, 2008, pp. 248–253.

[3] M. Jo, H. Y. Youn, and H. H. Chen, “Intelligent RFID tag detection using support vector machine,” *IEEE Trans. Wirel. Commun.*, vol. 8, no. 10, pp. 5050–5059, Oct. 2009.

[4] P. Evangelista, L. Santoro, and A. Thomas, “Environmental Sustainability in Third-Party Logistics Service Providers: A Systematic Literature Review from 2000–2016,” *Sustainability*, vol. 10, no. 5, p. 1627, May 2018.

[5] A. Marasco, “Third-party logistics: A literature review,” *Int. J. Prod. Econ.*, vol. 113, no. 1, pp. 127–147, May 2008.

[6] D. Pamucar, K. Chatterjee, and E. K. Zavadskas, “Assessment of third-party logistics provider using multi-criteria decision-making approach based on interval rough numbers,” *Comput. Ind. Eng.*, vol. 127, pp. 383–407, Jan. 2019.

[7] M. Farouk and A. Sutherland, “Principal component pyramids for manifold learning in hand shape recognition,” *ICT Express*, vol. 4, no. 2, pp. 63–68, Jun. 2018.

[8] H. I. Lee and J. W. Lee, “Online update techniques for projection based Robust Principal Component Analysis,” *ICT Express*, vol. 1, no. 2, pp. 59–62, Sep. 2015.

[9] X. Zhang, Y. Hu, K. Xie, S. Wang, E. W. T. Ngai, and M. Liu, “A causal feature selection algorithm for stock prediction modeling,” *Neurocomputing*, vol. 142, pp. 48–59, Oct. 2014.

[10] Y. Lee and H. Lee, “Application of factor analysis for service R&D classification: A case study on the Korean ICT industry,” *Expert Syst. Appl.*, vol. 38, no. 3, pp. 2119–2124, Mar. 2011.

[11] T. Inamoto, A. Ohno, and H. Murao, “An Approach of Vectorizing Shopping Paths Sensed by RFID Tags to Classify Retail Customers and Its Application with Principal Component Regression,” *Electron. Commun. Japan*, vol. 97, no. 7, pp. 63–72, Jul. 2014.

[12] H. Y. Liang, Y. T. Shieh, A. Sanjay, S. W. Yang, and S. De Lin, “Ensemble-based location tracking using passive RFID,” in *Proceedings - 2017 International Conference on Data Science and Advanced Analytics, DSAA 2017*, 2017, vol. 2018-Janua, pp. 420–428.

[13] G. L. Gragnani, S. Bergamaschi, and C. Montecucco, “Algorithm for an indoor automatic vehicular system based on active RFIDs,” *ICT Express*, vol. 3, no. 4, pp. 188–192, Dec. 2017.

[14] T. Keller, F. Thiesse, and E. Fleisch, “Classification models for RFID-based real-time detection of process events in the supply chain: An empirical study,” *ACM Trans. Manag. Inf. Syst.*, vol. 5, no. 4, 2014.

[15] C. S. Choong, A. F. A. Nasir, A. P. P. Abdul Majeed, M. A. Zakaria, M. A. Mohd Razman, and A. Azmi, “Comparison of Support Vector Machine and Friis Equation for Identification of Pallet-Level Tagging Using RFID Signal,” *ISCAIE 2020 - IEEE 10th Symp. Comput. Appl. Ind. Electron.*, pp. 215–219, 2020.

[16] G. Alfian, M. Syafrudin, B. Yoon, and J. Rhee, “False positive RFID detection using classification models,” *Appl. Sci.*, vol. 9, no. 6, 2019.

[17] E. de A. Moretti, R. Anholon, I. S. Rampasso, D. Silva, L. A. Santa-Eulalia, and P. S. de A. Ignácio, “Main difficulties during RFID implementation: an exploratory factor analysis approach,” *Technol. Anal. Strateg. Manag.*, vol. 31, no. 8, pp. 943–956, Aug. 2019.

[18] G. Abandah and N. Anssari, “Novel Moment Features Extraction for Recognizing Handwritten Arabic Letters,” *J. Comput. Sci.*, vol. 5, no. 3, pp. 226–232, Mar. 2009.

[19] Z. Ahmed, S. Yasmin, M. Nahidul Islam, and R. U. Ahmed, “Image processing based Feature extraction of Bangladeshi banknotes,” in *SKIMA 2014 - 8th International Conference on Software, Knowledge, Information Management and Applications*, 2014.

[20] M. Rani and Y. K. Meena, “An efficient feature extraction method for handwritten character recognition,” in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2011, vol. 7077 LNCS, no. PART 2, pp. 302–309.

[21] A. Zhao, G. Y. Tian, and J. Zhang, “IQ signal based RFID sensors for defect detection and characterisation,” *Sensors Actuators, A Phys.*, vol. 269, pp. 14–21, Jan. 2018.

[22] Motorola, “Item-level RFID Tagging and the Intelligent Apparel Supply Chain,” 2010.

[23] S. Evdokimov, “RFID and the Internet of Things: Technology, Applications, and Security Challenges,” *Found. Trends® Technol. Inf. Oper. Manag.*, vol. 4, no. 2, pp. 105–185, 2010.