Low-Density Polyethylene (LDPE) Food Packaging Defect Classification using Local Binary Pattern (LBP)

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Abstract. The motivation of this research is to automate the current food packaging inspection process by implementing the non-destructive approach. The current practices require human intervention where human vision tends to overlook the fault on the package resulting in accuracy dilemma. Human also may be exhausted due to repeated activities. This paper provides the primary phase for effective automation of the image classification solution implemented using Weka software. An evaluation of the performance of the Support Vector Machine (SVM), K-nearest Neighbour (KNN) and Random Forest (RF) classification models for Low-Density Polyethylene (LDPE) food packaging defect image classification using a small sample of dataset and Local Binary Pattern (LBP) as feature extraction algorithm is investigated. Four criteria have been used to evaluate the performance of each classification model which is accuracy, sensitivity, specificity and precision obtained from the confusion matrix table. The results indicate that SVM performs better than RF and KNN with 95% accuracy, 95% sensitivity, 72% specificity and 95% precision in classifying LDPE food packaging defect images.

1. Introduction
Polyethylene (PE) plastic is widely used as food packaging. There are many types of plastic and the commonly used material in plastic base is Low-Density Polyethylene (LDPE) which is often used in frozen food packaging [1]. Since the quality of food product relies on the quality of its package, packaging defects of LDPE material can reduce the quality of the product. The inspector conducted visual inspection; human vision tends to overlook the fault on the package resulting in accuracy dilemma because eyes can be affected with exhaustion due to the repetitive work of evaluating the details of the packages [2]. Therefore, to overcome the limitation of human inspection, an automated food packaging inspection using image processing approach is crucial to improve current practice. Features extraction is a crucial step because it is an important factor for the performance of the image classification accuracy [3]. Local Binary Patterns (LBP) has been used in many images processing research and it has successfully applied in texture descriptor. This method delivers a good performance based on a combination of structural method that portray texture by patterns that has regular appearance and located at the surface consistently and statistical method that represents texture...
that has irregular appearance and located at the surface inconsistently for texture analysis [4]. Due to the defect images used in this research such as wrinkled, channel leak and none affected seal are texture base, therefore, a texture feature used in this research which is LBP. To classify the features extracted by LBP, a comparison between Support Vector Machine (SVM), K-Nearest Neighbor (KNN) and Random Forest (RF) classifier will be conducted in this research. SVM is a classifier which has produces a good classification result in high-dimensional classification datasets. It also has a great computational efficiency [5]. Meanwhile, KNN is a simple classifier, yet efficient because it is a typical type of instance-based or memory-based learning scheme. KNN can also make the decisions based on dominant categories of k objects rather than a single object category [6]. RF is the most effective and efficient machine learning due to its high predictive precision and also proven to be successfully implemented in many fields [7]. Therefore, a comparison between these classifiers has been performed using LBP as a feature extraction to determine the best classifier model for the LDPE food packaging defect.

2. The classification method
The classification method consists of feature extraction using LBP, classification with SVM, KNN and RF.

2.1 Feature extraction with Linear Binary Pattern (LBP)
The feature extraction is a crucial step because it is an important factor for the classifier model performance and image classification accuracy [3]. These features are extracted from wrinkled, channel leak and none affected food packaging seal images due to the presence of repetitive patterns that depict the defects on the Low-Density polyethylene (LDPE) food packaging seal. LBP starts with dividing the image into cells such that for each cell, it is divided into 3 x 3 pixels. Next, pixel comparison is made according to its neighbour such as top-left and top-right. A circle is formed containing the comparison of the pixels. Value 1 is replaced if the value of the centre pixel is greater than the value of the neighborhood pixels; otherwise, value 0 is replaced in the cells. Then, a histogram is computed and normalized and lastly, the histogram of each cell is produced [8].

2.2 Classification based on supervised learning
Classification process is performed for computer to recognize the seal of food packaging image into wrinkled, channel leak or none affected based on the features that represent the image in numerical values. Three types of classifier are compared in this research which are Support Vector Machine (SVM), Random Forest (RF) and K-Nearest Neighbour (KNN). Classification algorithm differentiates data of unknown class into a particular type of class [9]. WEKA (Waikato Environment for Knowledge Analysis) suite is used to perform training and classification. This well-known suite of machine learning software design was developed by the University of Waikato.

2.2.1 Support Vector Machine (SVM)
SVM is proposed by Vladimir Vapnik and Corinna Cortes [10] utilizes the occurrence of an event with the previous occurrence of another event such that features are not dependent on each other. Sequential Minimal Optimization (SMO) from the WEKA suite using the same algorithm as SVM has been applied. Polynomial kernel is configured in WEKA tools due to its ability to separate the unseen (test) samples quite effectively by generating a nonlinear boundary between the infected and normal samples [11].

2.2.2 Random Forest (RF)
RF can be used both for regression and classification. The cumulative prediction error of a random forest is strongly associated with the size and density of individual trees within the forest. In addition to major randomness in the base models, trees and subsets of the predictor method, bagging can be
optimized to isolate the RF nodes of a tree [12]. RF is built based on selected decision trees at random
data sets, gets predictions for each tree and selects the best alternative by votes.

2.2.3 K-Nearest Neighbour (KNN)
KNN is a very simple algorithm that works based on the shortest distance from the test sample to the
training sample. KNN classifier was known for its simplicity, yet its performance can still match with
other complex classifiers. It is quite sturdy and adaptable to noise and large training data [6]. It uses
the neighboring classification technique for prediction, where it measures the distances. In WEKA
tools, Instance Based Learner (IBk) classifier, also known as KNN, uses Euclidean Distance (ED)
equation. Et is the most common distance function which represents the usual manner in which
humans think of distance in the real world [13].

3. Experiment Setup
The processes involve in defect detection are image acquisition, feature extraction and classification.
Figure 1 shows the framework of the proposed method for this research.

3.1 Image Acquisition
The most common defect on LDPE material is seal deficiency and leakage. The wrinkled seal is one of
the seal deficiencies. Meanwhile, channel leak is one of the leakage deficiencies [14]. Image of
wrinkle, channel leak and no defect package are acquired before analysis is performed using digital
camera shown in Figure 2.

![Figure 1. Framework of the proposed method.](image)

3.2 Feature Extraction
The purpose of features extraction process is to extract features in numerical value of an enhanced
food packaging image. This process is crucial because the numerical values are used for classification
process in order to identify the type of package defects. In this research LBP features of the food
packaging seal are extracted. MATLAB software has been used to extract the features into .csv files.
This file then will be converted into .ARFF file for further analysis in WEKA for classification
purpose. In this research, 3777 attributes of LBP features have been extracted from each image for
training and testing purpose. Each feature is labelled with the name of the defect as SVM, KNN and
RF are supervised machine learning classifiers.

![Figure 2. Sample images of LLDPE food packaging defect. The image (a) wrinkled seal, (b) and (c)
channel leak seal and no defect.](image)
4. Performance Evaluations
A 10-fold cross validation has been conducted where it is able to analyze the classification performance for each classifier which is SVM, Random Forest and KNN. Total images used in this research are divided into 10 parts where from the data collected, each part consists of 40 images of channel leak, no defect and wrinkle where the images were randomly selected. Accuracy specified the similarity of a variable to its true value where the amount of true and real negative cumulative images using confusion matrix. This confusion matrix represents with True Positive (TP) where actual label and predicted label is true, True Negative (TN) where actual label and predicted is false, False Positive (FP) where actual label is true, but the predicted label false and False Negative (FN) where actual label is false but the predicted label is true. In this research, four types of classification evaluation (sensitivity, accuracy, specificity and precision) are used to evaluate the performance of the three classifiers.

5. Results and Discussion
Table 1 shows that the accuracy of SVM is better than other two classifiers. The sensitivity, specificity and precision approximate the probability of the positive/negative label being true. Referring to Table 1, we can see that the sensitivity and specificity of SVM classifier is 0.95 and 0.72 respectively. For sensitivity, value 1 is considered as the best sensitivity predicted by the classifier and it shows that SVM manages to achieve 0.95 sensitivity compared to RF and KNN. It shows that SVM is a good classifier on classifying defect images. Meanwhile, specificity for SVM is 0.72 where this is not the best result achieved by SVM as value 1 indicates as the best result. However, a high specificity achieved by RF which is 0.895 and KNN is the lowest with 0.703. It shows that SVM is not the best classifier to classify other than true positive value. The last performance evaluation is on precision which is the highest precision achieved by SVM which is 0.95, followed by RF and KNN with 0.851 and KNN 0.85 respectively. The result of precision shows the high precision of SVM in classifying defect images. It shows that SVM is acceptable and the best classifier compared to RF and KNN in classifying defect images into three (3) classes which is channel leak, leakage and no defect.

Table 1. Performance measures (Accuracy, Sensitivity, Specificity, and Precision).

| Classifier   | RF     | SVM    | KNN    |
|--------------|--------|--------|--------|
| Accuracy     | 82.5%  | 95%    | 84.16% |
| Sensitivity  | 82.5%  | 95%    | 84.2%  |
| Specificity  | 89.5%  | 72%    | 70.3%  |
| Precision    | 85.1%  | 95%    | 85%    |

SVM misclassifies three channel leak and three wrinkle defects due to the similarity of the texture on channel leak and wrinkle defect. For example, the image is false under channel leak image; however, it is falsely classified as wrinkle. This is due to majority of the image consist of wrinkle and only a small portion of the image consist of channel leak. Besides, the dataset itself has two defects while SVM is trained to classify either one defect. However, SVM is still able to produce a high value of accuracy compared to RF and KNN with a larger number of falsely classified. Therefore, SVM can be accepted as the best classifier to detect defect on LDPE food packaging.

6. Conclusions and Future Work
This research presents classification of LDPE food packaging defect by comparing SVM, RF and KNN classifiers using WEKA tools. It shows that the LBP texture features are suitable to be used with SVM for LDPE food packaging defect classification. The accuracy achieves using SVM model is 95% using 3777 features extracted from LBP on 120 images. In the future, other parameters associated with classifiers in the WEKA tool will be used and explored for optimizing the performance of classifiers for text region classification to meet the challenges incurred in real time applications.
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