Performance evaluation of machine learning algorithms for meat freshness assessment

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ABSTRACT

In meat industry, a non-destructive evaluation and prediction of meat quality attributes is highly required. Artificial vision technology is a powerful and widely used tool for meat quality evaluation because of reliability, reproducibility, non-invasiveness, and non-destructiveness. Machine learning methods are a fundamental and crucial part of artificial vision technology. Their choice is critical in determining successfully the quality of meat. The goal of this paper was to compare the performance of three artificial intelligence-based methods to evaluate the beef meat freshness. In this research, a dataset of beef meat samples images was used to extract the color and texture features. Different methods including the support vector machines (SVM), k-nearest neighbor (KNN), and naïve Bayes (NB) algorithms were applied to determine the freshness of samples. The accuracy rates of KNN, SVM and NB algorithms were obtained about 92.59%, 90.12% and 87.65%, respectively. The results show that the KNN provides the highest classification rates against SVM and NB algorithms.

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1. INTRODUCTION

More than ever before, the assessment of the quality of meat has become a matter of great concern for both researchers and consumers. Traditional microbiological techniques are efficient but laborious, time consuming, demand qualified human, destructive and applicable only for off-line control [1]. On the contrary, non-destructive detection techniques such as e-eye, e-nose and e-tongue are a growing field based on physics, electronics, computer science and machine learning algorithms [2]. These techniques are rapid, repeatable, considered environmentally friendly because they eliminate the need for chemical reagents [3], cost-efficient and suitable for online assessment [4], [5]. They have been widely used to control food quality such as meat [6], fruits [7], oil [8], fish [9] vegetable [10], and milk products [11].

Artificial vision technology has been widely applied to detect the quality of meat due to its low cost and high efficiency [2]. In brief, artificial vision technology is a structure that is able to offer a precise physical explanation of an object over image analysis [12]. The image captured by the physical sensor is processed and then classified using machine learning methods. Therefore, machine learning methods are fundamental and crucial [13]. Machine learning is a type of artificial intelligence that enables systems to learn from their experiences and progress without the need for explicit programming. It seeks to create algorithms that have access to data and can utilize it to educate themselves [10]. Machine learning includes data pre-processing, feature engineering, model selection, assessment, optimization methods, unsupervised, and supervised algorithms [13]. These algorithms are used for data classification and regression. In classification, several algorithms can produce optimal performance for a given problem, so, in order to get the best one, a comparison should be made between these algorithms.

In food industry, several studies have compared the ability of machine learning algorithms to classify and predict the quality of meat with a good accuracy. Teimouri *et al*. [14] developed a novel on-line approach based on combination of machine vision techniques and linear/nonlinear classifiers to classify chicken meat automatically. Artificial neural networks (ANN), linear discriminant analysis (LDA), and partial least squares regression (PLSR) algorithms were implemented in order to classify the data. The results show that ANN provided the best classification rate. An evaluation of machine vision technology using the ANN classifier was achieved in a sorting machine for online classification of samples. The total accuracy of sorting in the conveyor with highest speed about 0.2 ms^{-1} was 93%.

Xu *et al*. [15] suggested a novel olfactory visualization system that is able to detect the beef meat freshness using chemometrics and colorimetric approaches. Four qualitative models, i.e. random forest, support vector machines (SVM), extreme learning machine, and k-nearest neighbor (KNN) have been tested on the volatile basic nitrogen and the total bacterial count characterizing the beef meat quality. Obtained results are accuracies of 96% for the training set and 95% for the prediction set using SVM method.

Chanasupaprakit *et al*. [16] proposed a method to control fake beef by proposing a virtual expert to support in meat examination. Following image processing steps, the training model was constructed with the convolutional neural networks (CNN) and SVM algorithms. Obtained classification performance was 98% for both beef and pork meat.

Luo *et al*. [17] used the beef viscoelasticity to assess its quality based on the airflow-3D image processing method and artificial intelligence algorithms. The best prediction models for freshness parameters were determined by building regression models based on viscoelastic properties. Several algorithms have been proposed: decision tree regression (DTR), SVM regression (SVR), backpropagation neural network (BPNN), and PLSR. Results show that SVR and BPNN provide best prediction performances.

Sun *et al*. [18] predicted the tenderness of beef based on multispectral texture parameters and color images. SVM and stepwise multiple regression equation were used to construct prediction models for beef tenderness. For both color and multispectral parameters, the SVM algorithm gives best prediction rates i.e 100% for color images and 91% for multispectral images.

In our previous work [19], the quality of beef meat was assessed based on texture features, color features and texture associated to color features using probabilistic neural network (PNN) and LDA algorithms and an embedded device. Results demonstrate that PNN leads to the best classification rate when associating color and texture parameters. This paper implemented and compared the performances of KNN, SVM and NB algorithms in order to determine the quality of beef meat using color and texture features and an embedded system. This paper is organized as follow: section 2 describes the process of meat samples preparation, the experimental setup and the image acquisition and processing steps. Section 3 presents machine-learning algorithms applied to classify the samples. Section 4 shows the obtained results. Conclusion is presented in section 5.

2. METHOD

2.1. Sample preparation

The samples used in this experiment were obtained from various providers from the local market of Beni Mellal (Morocco) city. After being refrigerated during transportation, the samples were placed in plastic boxes and maintained at 4±1 °C for nine days in the laboratory [20]. For each measurement, a sample was taken from the refrigerator and placed under the camera in order to capture the images.

2.2. Experimental testbed overview

The experimental platform consists of the camera system, the processing platform, and the human machine interface (HMI). The GP1503C device from New Electronic Technology's GigEPRO camera series was used to take the beef photographs. The resolution of the images was 2592×1944 pixels. The GigE Vision protocol, an Ethernet-based communication standard for sending uncompressed images, is supported by this camera. This protocol was used for image transferring between the camera and the processing platform. The processing platform, presented in Figure 1, was based on the EVM6678 evaluation board from Texas Instruments (TI) [19], [20], while a laptop was used as a HMI. The rapid processing and the portability of the suggested embedded system allow for on-site and real-time use.

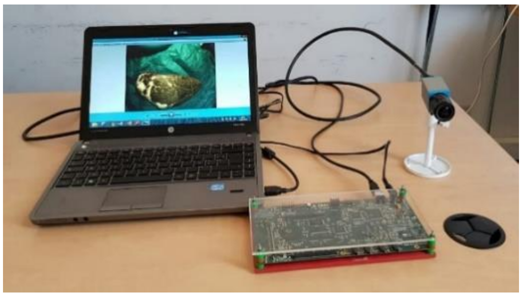


Figure 1. Experimental platform

2.3. Image processing overview

Following the capture of images, the region of interest (ROI) was represented by cropping the images into a 512×512 window. After that, the ROI pictures were transformed into the Hue, Saturation, Intensity (HSI) color space. Only the saturation channel was taken into account because it has been shown to be quite successful for beef meat in previous research [20].

The saturation images were decomposed by the fast wavelet transform [19] in order to calculate the texture features. In addition, six parameters of color features including the mean, standard deviation, variance, interquartile range, skewness and kurtosis were calculated from the saturation's images. Consequently, a global dataset of color and texture was formed. Finally, KNN, SVM and NB machine algorithms were implemented to classify beef meat samples. Figure 2 gives an overview of all the classification process.

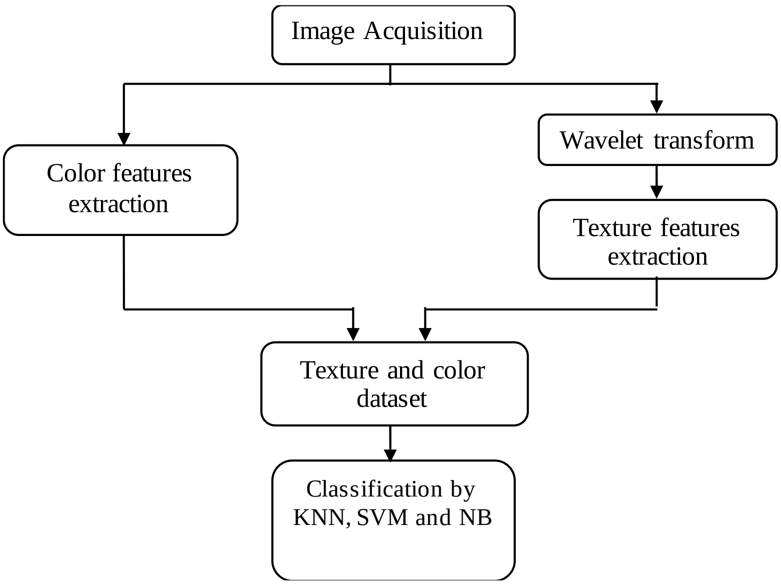


Figure 2. Overview of the proposed method of beef meat classification

3. MACHINE LEARNING ALGORITHMS

3.1. KNN algorithm

Introduced for the first time in 1950s and became popular in 1960s, this supervised method has widely been used in classifying data due to its simple implementation and distinguished performance [21]. It is predicated on the notion that labels or values on similar data points typically correspond. First, the algorithm needs a labelled dataset for training. Whenever a new sample has to be classified, KNN is calculated from the training dataset based on the distance that separate the new sample and each point in the dataset.

In the literature, the distance can be calculated based on diverse methods. The choice of one (or more) of them depends on the data studied. In this study, the Euclidean distance was used with (1).

$$d(x,y) = \sqrt{\sum_{k=1}^{N}(a_k - b_k)^2} \quad (1)$$

N represents the number of attributes, a_k and b_k are respectively, two points that is wanted to be learnt the distance between them.

3.2. Support vector machines

Based on statistical learning theory, SVM is a supervised machine learning method. Since Cortes and Vapnik [22] first introduced it, it has been widely utilized. Its grounding in mathematics makes it one of the most efficient categorization engines. SVM classifies data using the linear or non-linear kernel function. SVM tries to find an optimal hyperplane with maximum margin. SVM translates the data into a high-dimensional feature space and conducts the classification if the data is not linearly separable. Equation (2) provides the equation of the separating hyperplane.

$$W.X + b = 0 \quad (2)$$

W is the hyperplane's normal, b is the bias, and X is a point on the hyperplane. The margin is maximized as a result of minimizing W.

3.3. Naïve Bayes algorithm

Naïve Bayes (NB) is a well-known probabilistic supervised algorithm used for solving classification problems [23]. The algorithm relies on the Bayes theorem, which is frequently referred to as Bayes' law or rule. It is employed to calculate a hypothesis's likelihood using prior knowledge. The conditional probability determines this. As stated, the NB theorem is:

$$P(X|Y) = \frac{P(X)P(Y|X)}{P(Y)} \quad (3)$$

Both X and Y are independent. The probability of X after Y has already occurred is denoted as $P(X|Y)$. The probabilities of two independent X and Y are denoted by $P(X)$ and $P(Y)$. The probability of Y after X has already occurred is $P(Y|X)$.

3.4. Software tools

Initially, image processing, wavelet transform, statistics and machine learning toolboxes of MATLAB software, 2021b version, have been used to execute the data processing presented in Figure 2. Then, The MATLAB Coder application was performed to convert the developed MATLAB script to an embedded C code. Finally, this code was implemented on the C6678 DSP using code composer studio (CCS) integrated development environment (IDE) from TI. The compiler optimization levels (Pipeline for instructions) have been enabled in order to minimize the processing time. Furthermore, a memory management strategy has been implemented to minimize data access time. This strategy maximizes the use of internal and cache memories instead of DDR external memory.

4. RESULTS AND DISCUSSION

In this work, the confusion matrix was applied to evaluate the performance of the KNN, SVM, and NB algorithms. It represents the information about the freshness of beef meat samples where each row of the matrix represents an actual class and each column represents a predicted class. Moreover, five parameters were employed to characterize the performance of the algorithms: accuracy, recall, precision, specificity and F1-score. Each of these values were between 0 and 1. The performance measures were computed using (4)-(8).

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \quad (4)$$

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

$$Precision = \frac{TP}{TP+FP} \quad (6)$$

$$Specificity = \frac{TN}{TN+FP} \quad (7)$$

$$F1\ score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (8)$$

where, TP is the number of true positives (fresh samples) that are fresh and classified as fresh. TN is the number of true negatives (spoiled samples) that are spoiled and classified as spoiled. FP is the number of false positives (spoiled samples classified as fresh). FN is the number of false negatives, (fresh samples classified as spoiled).

The leave-one out cross-validation was applied to evaluate the model. It is a statistical method used to avoid overfitting and to estimate the ability of machine learning models on a limited dataset. The leave-one-out cross-validation routine works by withdrawing one observation at one time to be used as a validation data, recalculating the classification function using the remaining data (training data), and then predicting the omitted observation. This routine is repeated until each observation in the dataset is used once as validation data [24].

Figures 3(a), 3(b) and 3(c) illustrate the confusion matrix rates of KNN, SVM and NB algorithms respectively based on texture and color features. From Figure 3(a) it can be noticed that six samples were misclassified, five from fresh samples and one from spoiled sample, using KNN algorithm ($K = 4$). Indeed, according to previous microbiological researches [25]–[27], the beef samples that have undergo six days of cold storage (4 °C) are considered fresh. Moreover, Figure 3(b) shows that eight samples were misclassified four from fresh samples and four from spoiled samples using SVM algorithm. Finally, Figure 3(c) shows that ten samples were misclassified eight from fresh samples and two from spoiled samples using NB algorithm. The errors of misclassification can be explained by the fact that the color of samples in the sixth day and seventh day of cold storage visually appears more similar to each other as shown in Figure 4(a) and (b). To overcome this limitation, the image acquisition process will be improved in future works.

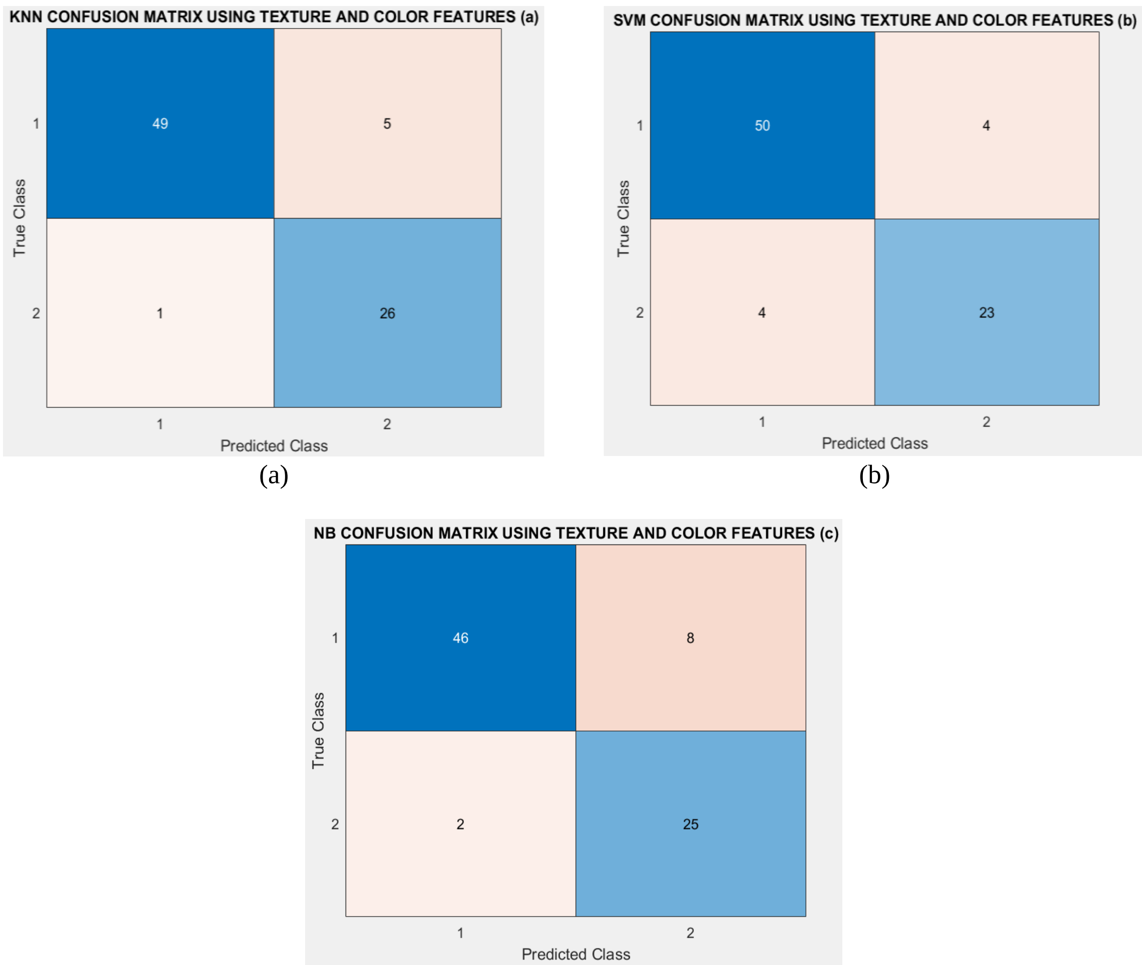
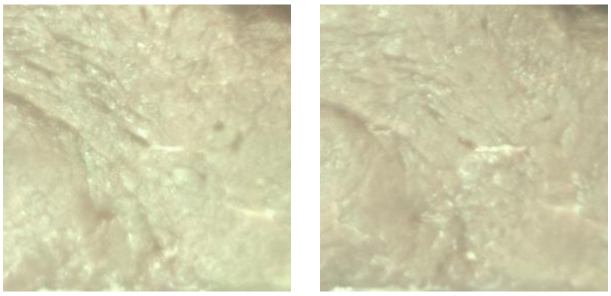


Figure 3. Confusion matrix of classification results using (a) KNN, (b) SVM, and (c) NB



(a) (b)

Figure 4. Misclassification examples of images of samples at (a) day 6 and (b) day seven of cold storage

Table 1 represents the accuracy, recall, precision, specificity, and F1-score values of KNN, SVM and NB algorithms. It shows that the lower accuracy rate was 87.65%, which was obtained using NB, and the highest accuracy rate was 92.59%, which was obtained using KNN. Furthermore, an accuracy rate about 90.12% was obtained using SVM. Moreover, for the recall rates, SVM scored the highest rate which was about 92.59%, and the lower rate was provided using NB which was about 85.18%. KNN provided a recall rate about 90.74%. Regarding the precision rates, KNN provided the highest which was about 98%, the lower rate was scored using SVM and was about 92.59% and NB provided a rate about 95.83%. For the specificity rates, the highest rate was provided using KNN which was about 96.25%, and the lower rate was scored using SVM and was about 85.18%. NB provided a rate about 92.59%. Finally, for the F1 score rates, the highest was obtained using KNN which was about 94.23% and the lower rate was scored using NB 90.19%. SVM provided a rate about 92.59%.

The overall results show that the KNN algorithm provides the best classification rates in term of accuracy, precision, specificity, and F1-score against SVM and NB algorithms. In addition, the accuracy rates provided by KNN, SVM and NB algorithms are much higher than the accuracy rate obtained in our previous work using LDA algorithm, which did not exceed 82.7% using the same dataset.

Table 1. Classification results using KNN, SVM, and NB algorithms

Classifier	Accuracy (%)	Recall (%)	Precision (%)	Specificity (%)	F1 score (%)
KNN	92.59	90.74	98	96.29	94.23
SVM	90.12	92.59	92.59	85.18	92.59
NB	87.65	85.18	95.83	92.59	90.19

5. CONCLUSION

The present paper proposed a comparison of the performance of three classification methods namely SVM, KNN, and NB to classify beef meat samples using texture and color features. Thus, eighty-one images were captured, and the saturation channel of the HSI color system was used to form the dataset. The wavelet transform was applied to the saturation images to extract texture features and six statistical parameters were calculated to represent the color features. KNN, SVM, and NB algorithms were used to classify beef meat samples into fresh and spoiled. The obtained results show that compared to SVM and NB, the KNN algorithm provides successful classification rates about 92.59%, 90.74%, 98%, 96.29%, 94.23% of the accuracy, recall, precision, specificity and F1 score respectively. The results show that the choice of machine learning algorithms is critical and important to determine successfully the quality of beef meat with a portable device based on artificial vision technology.

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