Iran J Public Health, Vol. 45, No.10, Oct 2016, pp.1276-1287

Original Article

A Bio Medical Waste Identification and Classification Algorithm Using Mltrp and Rvm

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(Received 22 Mar 2016; accepted 10 Aug 2016)

Abstract

Background: We aimed to extract the histogram features for text analysis and, to classify the types of Bio Medical Waste (BMW) for garbage disposal and management.

Methods: The given BMW was preprocessed by using the median filtering technique that efficiently reduced the noise in the image. After that, the histogram features of the filtered image were extracted with the help of proposed Modified Local Tetra Pattern (MLTrP) technique. Finally, the Relevance Vector Machine (RVM) was used to classify the BMW into human body parts, plastics, cotton and liquids.

Results: The BMW image was collected from the garbage image dataset for analysis. The performance of the proposed BMW identification and classification system was evaluated in terms of sensitivity, specificity, classification rate and accuracy with the help of MATLAB. When compared to the existing techniques, the proposed techniques provided the better results.

Conclusion: This work proposes a new texture analysis and classification technique for BMW management and disposal. It can be used in many real time applications such as hospital and healthcare management systems for proper BMW disposal.

Keywords: Bio medical waste, Median filter, Sensitivity, Specificity

Introduction

Bio Medical Waste (BMW) originates from human, animal health care, medical teaching facilitates, medical research, biological laboratory waste and other facilities. A part of that waste stream is infectious or potentially infectious and it must be appropriately managed to defend the sanitation and healthcare personnel. Normally, the BMWs (1-3) are regulated and managed according to various standards and protocols in different countries. In health care facilities, the wastes are generated during improper management, which causes a direct health impact in the community, the environment and the health care workers. BMW is a dangerous health hazard to the public, hospital, health care units, flora and fauna of the area. BMW must be stored in a secure environment at all times, whenever possible, BMW should not be mixed with chemical, radioactive or other laboratory trash. Containers for BMW must be appropriate for its contents, there are different kinds of containers, and bags are available for the containment and disposal of BMW (4). The Government of India specifies that BMW is a part of hospital hygiene and maintenance activities. The World Health Organization (WHO) has categorized the BMW into eight categories, includes,

- General Waste
- Infectious or dangerous waste

- Radioactive
- Chemical
- Pathological
- Pressurized containers
- Pharmaceuticals

Preprocessing is an essential step in image processing applications, which eliminates the irrelevant noises in the given input image. Median filters are widely used in many images processing application, because it provides excellent noise reduction capabilities for noise removal. In this paper, an improved median filtering technique is applied to remove the noises in the given BMW image. After denoising, the texture features of the preprocessed BMW image is extracted based on the histogram value by using the MLTrP.

In this research, the type of BMW is identified and classified with the help of MLTrP and the RVM classifier. Image processing algorithms apply local and global operations on an input image for some particular reasons, such as, noise elimination, edge detection and contrast stretching. The Local Binary Pattern (LBP), Local Derivative Pattern (LDP) and Local Tetra Pattern (LTP) are the existing feature extraction approaches. These techniques are mainly used to extract the information based on the distribution of edges, coded using only two directions such as, positive and negative directions. The performance of these methods can be enhanced by differentiating the edges in more than two directions. In order to overcome this limitation, the MLTrP extraction method is used in this work. The MLTrP is a three direction code that illustrates the spatial structure of the local texture by using the direction of the central gray pixel. BMW should be classified according to their source, type and risk factors (5). In this paper, MLTrP for BMW classification is proposed based on a diagonal, horizontal and vertical direction. The text on is an essential concept in texture analysis, applied to develop effectual models in texture recognition. Moreover, the extraction of pattern is used to classify each pixel using tetra direction and the extraction of magnitude pattern is collected using the magnitude of derivatives. There are different classification techniques are available for an efficient image classification. Some of the existing classification techniques compared in this paper is, Artificial Neural Network (ANN) (6), decision tree (7), Support Vector Machine (SVM) (8) and fuzzy measure (9). ANN is a non-parametric universal classifier and it efficiently handles the noise input. The disadvantages of this technique are, its computational rate is high, it is semantically poor, it has the over fitting problem and it consumes more time for training. Decision tree is a non-parametric training data that provides hierarchical associations between input variables to forecast class membership. It is simple and the computational efficiency is good, which are major advantages of this technique. It becomes more complex, when various values are correlated that is the main limitation of this approach.

SVM is an unsupervised learning classifier that gains the flexibility in the form of threshold and contains a non-linear transformation. The advantages of this method are, it has lesser computational complexity and it is simple to manage the decision rule complexity. The disadvantages of this technique are, the resultant transparency of SVM is low, it consumes less time for training, the structure of this technique is not easy to understand and the determination of optimal parameters are is more complex. In order to overwhelm these drawbacks, the RVM classification technique is used in this paper.

After extracting the texture features, the RVM classifier is used to classify the BMW wastages. RVM is a prevalent choice for classification task, which provides more advantages over SVM. In this analysis, it is mainly used for the classification of input BMW image. After classification, the types of wastages are identified in order to segregate and dispose the BMW properly. In this analysis, four types of wastages are identified and classified such as, human body parts, plastics, cotton and liquids. The main intention of this work was to define BMW and to provide information about the identification and classification of this waste stream. For this purpose, the MLTrP with RVM classification method is proposed in this paper.

We aimed to extract the histogram features for text analysis and, to classify the types of BMW for garbage disposal and management.

Methods

Here, the MLTrP and RVM were used to efficiently extract and classify the histogram features of BMW image. The main aim of this work was to extract the histogram features from the BMW image and to classify the type of BMW as plastic, cotton, liquid or human body parts. The proposed BMW image classification system was designed at the year of 2014 using the MATLAB tool with certain Garbage images. This paper introduced a new framework for proper garbage disposal and management.

Preprocessing

Preprocessing images generally involves eliminating background noise, stabilizing the intensity of the specific particle images, eliminating reflections and masking portions of images. Image preprocessing is the method of increasing data, images proceeding to computational processing. The preprocessing of BMW at the source of generation is the initial step, but is an essential step in health care waste management. In this research, the median filter is used to preprocess the BMW image. Median filtering is a nonlinear method, mainly used to remove the noise from images. It is very effective and extensively used technique in noise removing while preserving edges. Median filter is one of the main building blocks in image processing applications, which adequately removes the salt and pepper type of noises. It removes the noises in the BMW image by moving through the image pixel by pixel. The pattern of neighbors is referred as window, which slides pixel by pixel over the entire BMW image. Initially, the median is calculated by arranging all pixel values from the window into numerical order. After that, it replaces each value as the median value of the neighboring pixels. Fig. 1 shows the process of median filtering based BMW image preprocessing.

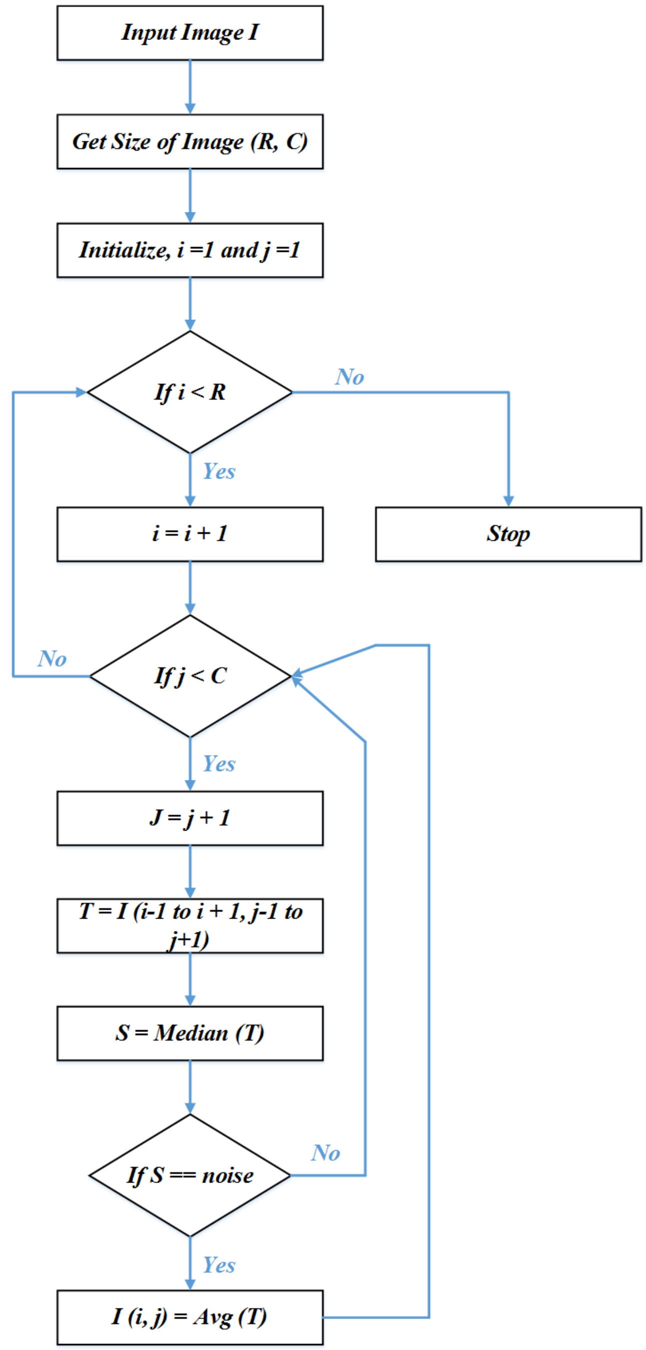

Fig. 1: Process of Median filtering

Initially, the BMW image is given to the input and the noises present in this image is removed by using the median filtering technique. Then, the texture features of the denoised image are extracted by using the MLTrP technique. In this stage, the patterns are extracted and the encodedmagnitude patterns are calculated based on the pixel directions (0°, 45° and 90°). Hence, the histogram features are selected and given to the input of RVM classifier. Finally, it classifies the BMW image into human body parts, cotton, plastics and liquid wastages.

Feature Extraction

Feature extraction is the process of capturing the visual content of images for indexing and retrieval. Feature extraction involves facilitating the amount of resources needed to represent a large set of data exactly. The aim of feature extraction is to represent the raw image in its reduced form to facilitate decision-making process such as pattern classification. Feature extraction is an essential step to get high classification rate. A set of features are extracted in order to allow a classifier to identify the normal and abnormal pattern. The BMW image region is determined by the way of gray levels are distributed over the pixels in the region. The properties of the BMW image region are quantified by exploiting space relations underlying the gray level distribution. In this paper, the features of the input BMW image are extracted by using the MLTrP. Fig. 2 shows the overall flow of the proposed MLTrP based feature extraction and RVM based classification.

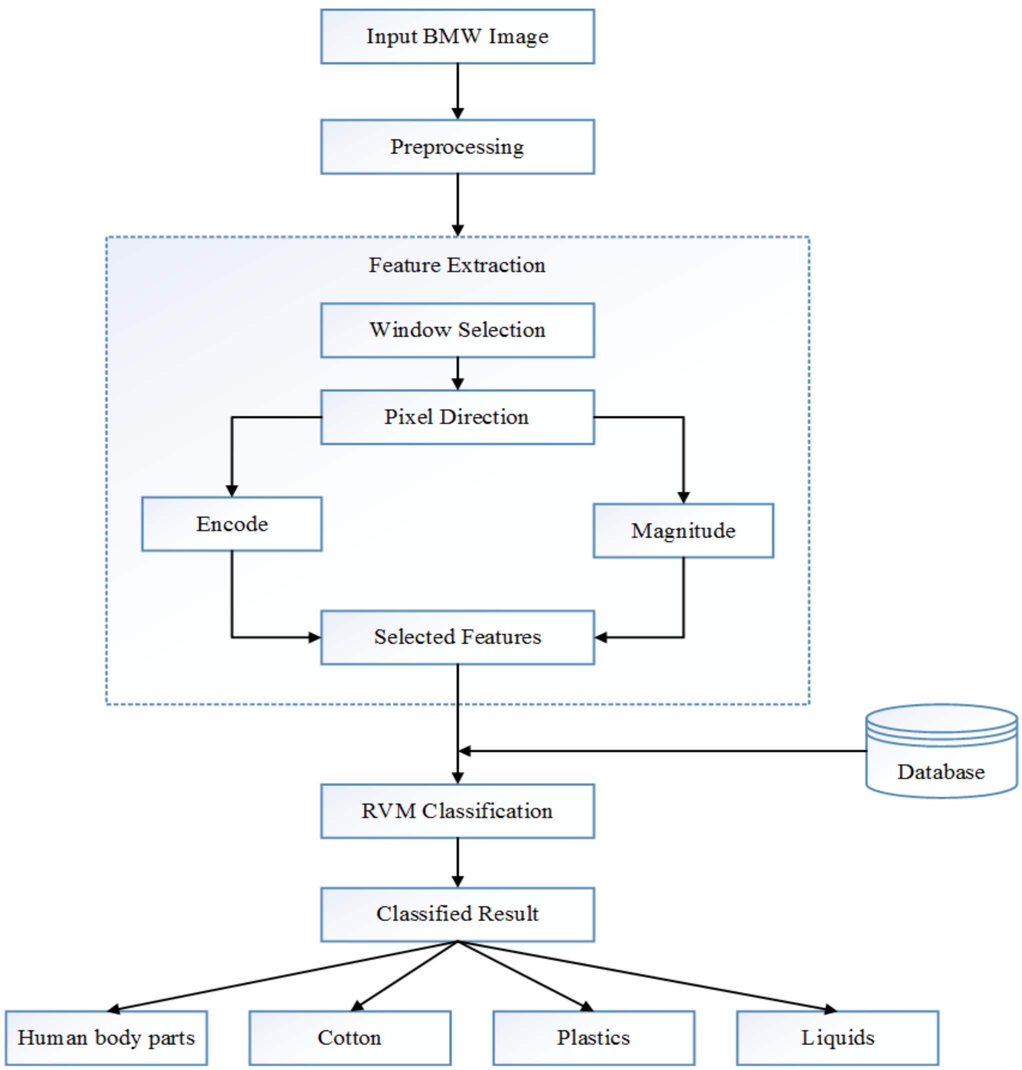

Fig. 2: Overall flow of the proposed BMW identification and classification

MLTrP

In the field of texture feature extraction and classification, the MLTrP is a stepping stone. It is mainly used to build the relationship between the central pixel and the neighboring pixels by calculating the gray level difference. The MLTrP encodes the input BMW image by calculating the horizontal and vertical directions of each pixel. It codes the relationship based on the direction of the central pixel p_c and neighbors. The directions are calculated by combining *(n-1)th* – order derivatives of the 0°, 45° and 90°directions. The first order derivatives along 0°, 45° and 90° directions are denoted as,

$$D_\theta^1\,(n_p)|\theta = 0°, 45°, 90°$$

Let n_c denotes the central pixel in image *D*, n_h indicates the horizontal neighborhood, n_v indicates the vertical neighborhood and n_d represents the diagonal neighborhoods of n_c respectively. Then the first order derivatives at the center pixel is calculated as,

$$D_{0°}^1(n_c) = D(n_h) - D(n_c) \quad [1]$$

$$D_{45°}^1(n_c) = D(n_d) - D(n_c) \quad [2]$$

$$D_{90°}^1(n_c) = D(n_v) - D(n_c) \quad [3]$$

The center pixel's direction is calculated as,

$$D_{Dir}^1(n_c) = \begin{cases} 1, D_{0°}^1(n_c) \geq 0 \text{ and } D_{45°}^1(n_c) \geq 0 \text{ and } D_{90°}^1(n_c) \geq 0 \\ 2, D_{0°}^1(n_c) < 0 \text{ and } D_{45°}^1(n_c) \geq 0 \text{ and } D_{90°}^1(n_c) \geq 0 \\ 3, D_{0°}^1(n_c) < 0 \text{ and } D_{45°}^1(n_c) \geq 0 \text{ and } D_{90°}^1(n_c) < 0 \\ 4, D_{0°}^1(n_c) \geq 0 \text{ and } D_{45°}^1(n_c) \geq 0 \text{ and } D_{90°}^1(n_c) < 0 \\ 5, D_{0°}^1(n_c) \geq 0 \text{ and } D_{45°}^1(n_c) < 0 \text{ and } D_{90°}^1(n_c) \geq 0 \\ 6, D_{0°}^1(n_c) < 0 \text{ and } D_{45°}^1(n_c) < 0 \text{ and } D_{90°}^1(n_c) \geq 0 \\ 7, D_{0°}^1(n_c) < 0 \text{ and } D_{45°}^1(n_c) < 0 \text{ and } D_{90°}^1(n_c) < 0 \\ 8, D_{0}^1(n_c) \geq 0 \text{ and } D_{45°}^1(n_c) < 0 \text{ and } D_{90°}^1(n_c) < 0 \end{cases}$$

[4]

From equation [4], it is apparent that the possible direction for each center pixel can be 1, 2, 3, 4, 5, 6, 7 or 8 and eventually, the image is converted into eight directions. The sec order $MLTrP^2(n_c)$ is defined as follows,

$$MLTrP^2(n_c) = \begin{Bmatrix} f_8\left(D_{Dir}^1(n_c), D_{Dir}^1(n_1)\right), f_8\left(D_{Dir}^1(n_c), D_{Dir}^1(n_2)\right), \ldots \\ f_8\left(D_{Dir}^1(n_c), D_{Dir}^1(n_p)\right) \end{Bmatrix} \quad | \, p = 8 \quad [5]$$

$$f_8\left(D_{Dir}^1(n_c), D_{Dir}^1(n_p)\right) = \begin{cases} 0, D_{Dir}^1(n_c) = D_{Dir}^1(n_p) \\ else, D_{Dir}^1(n_p) \end{cases} \quad [6]$$

The 8-bit tetra pattern for each central pixel is obtained from equations [5] and [6]. Then, all patterns are separated into 8 parts based on the direction of center pixel. Where, the direction of the center pixel $(D_{Dir}^1(n_c))$ is obtained from equation [4]. Hence, $MLTrP^2|\,Direction = 2, 3, 4, 5, 6, 7, 8$

$$= \sum_{p=1}^{p} 2^{(p-1)} * f_8(MLTrP^2(n_c))|Direction = 2, 3, 4, 5, 6, 7, 8 \quad [7]$$

$$f_8\left(MLTrP^2(n_c)\right)|Direction = \phi = \begin{cases} 1, if \; MLTrP^2(n_c) = \phi \\ 0, else \end{cases} \quad [8]$$

Where, $\phi = 2, 3, 4, 5, 6, 7, 8.$ similarly, the other tetra patterns for remaining 8 directions of center pixels are converted to binary patterns. Finally, 56 (8×7) binary patterns are taken. Fig. 3 shows the process of histogram feature extraction with the help of MLTrP.

Input: Preprocessed BMW image.

Output: 8-bit tetra pattern.

Step 1: Initialize 5×5 window and project it on our input image.

Step 2: Choose 8 neighboring pixels around the central pixel.

Step 3: Compare Center pixel value with its neighbor for angle of 0°, 45° and 90°.

Step 4: Create Phasor diagram for the center pixel.

Step 5: Compare the central pixel value with its 8 neighboring pixels.

Step 6: Compare Phasor with neighboring pixels and form tetra pattern.

Step 7: Separate each tetra pattern to form binary representation.

Step 8: If the value of the central pixel matches with the neighboring pixels, then

Replace it by '0',

Else

Replace it by '1'.

Step 9: Finally, this gives the values of 8-bit tetra pattern for every pixel and rearrange it to for decimal value.

Fig 3: Process of MLTrP based feature extraction

The magnitude component of the MLTrP provides more useful information for texture feature classification. Exploiting the combination these patterns provides better indications, which are not apparent in any of the individual component. The magnitude pattern of MLTrP feature extraction is shown in Fig. 4.

Fig. 5 illustrates tetra pattern calculation for the center pixel direction 1 by using the direction of neighbors. The direction of blue arrows represents the center pixel and the black arrows represent the neighboring pixels. Here, we take 57 patterns (i.e. 8 X 7), 56 tetra patterns and 1 magnitude pattern. Hence, we increase the number of patterns for texture feature extraction. The traditional algorithms find the tetra pattern in 4 directions, but in this work we take 8 directions.

Input: Preprocessed BMW image.

Output: Magnitude Pattern

Step 1: Initialize 5×5 window and project it on our input image.

Step 2: Choose 8 neighboring pixels around the central pixel.

Step 3: Calculate distance between two pixels at directions of 0°, 45° and 90°.

Step 4: Then, compare the difference between them. If the distance value of a pixel is less than the distance value of the neighboring pixels means replace the magnitude pattern value as 1.

Step 5: Otherwise, replace the magnitude pattern value as 0.

Step 6: Finally, this gives the values of 8-bit tetra pattern for every pixel and rearrange it to decimal value.

Fig 4: Process of Magnitude pattern extraction

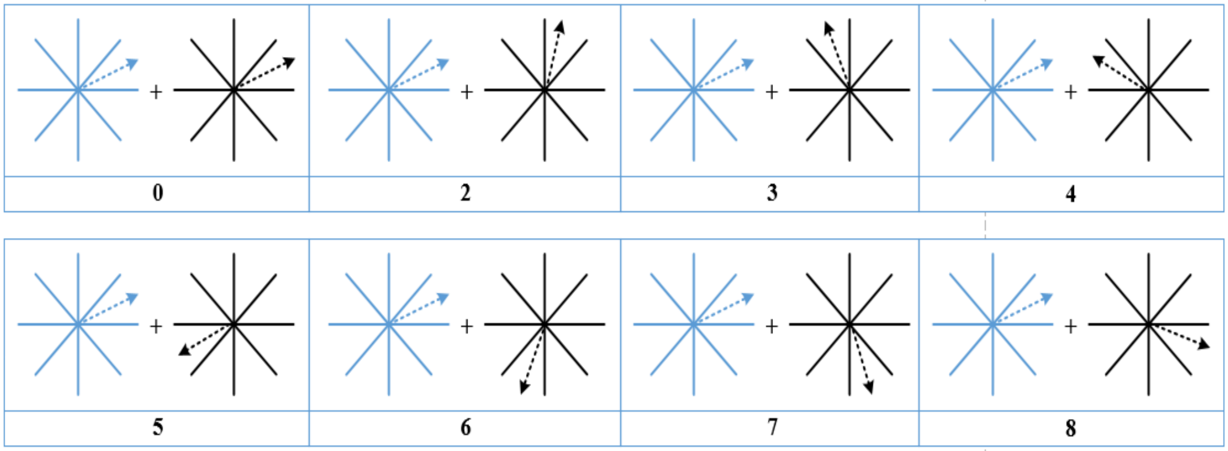

Fig. 5: Phasor diagram for tetra pattern calculation

RVM Classification

RVM is a sparse learning algorithm that is similar to SVM, which is capable of delivering a fully probabilistic output. The advantages of RVM yield a decision function that is much sparser than SVM, while maintaining its classification accuracy. RVM is a convex quadratic program, which provides a probabilistic interpretation of the output vector machine. The idea of RVM is that the input data are mapped to a high dimensional feature space by kernel function.

Given a set of data $\{a_i, b_i\}_{i=1}^{n}$, where a_i is the input vector and b_i are their corresponding outputs. The output of RVM is illustrated as follows,

$$b(a) = \sum_{i=1}^{n} w_i f(a, a_i) + w_0 \quad [9]$$

Where, $w = [w_0, \dots w_i]$ represents the weight vector, $f(a, a_i)$ represents the kernel function. In RVM, Gaussian kernel is used as the encountered kernel, expressed as follows,

$$f(a, a_i) = exp\left[-\frac{||a-a_i||^2}{2\sigma^2}\right] \quad [10]$$

Where, σ represents the width of Gaussian kernel. The likelihood of the dataset can be expressed by using,

$$p(b|w, \sigma^2) = (2\pi\sigma^2)^{-\frac{n}{2}} exp\left[-\frac{1}{2\sigma^2}||b-\rho||^2\right] \quad [11]$$

Where,

$$\rho(a_i) = (1, f(a_i, a_1), f(a_i, a_2), \dots, f(a_i, a_n))' \quad [12]$$

An explicit prior probability distribution over the weights to improve the generalization ability of RVM model, defined as follows,

$$p(w|x) = \prod_{i=1}^{n} N(w_i|0, x_i^{-1} \quad [13]$$

Where, x represents a hyper-parameter vector. Thus, a classifier function of relevance vector machine can be expressed by,

$$b(a) = \rho'(a)(\sum_{i=1}^{n} x_i \rho(a_i)) \quad [14]$$

In this analysis, the RVM classifier is mainly used to classify the types of wastages such as, human body parts, cotton, plastics and liquids. The merits of RVM classifier over SVM are,

- RVM classifier requires a small amount of relevance vector than the SVM.
- When compared to SVM, it needs less testing time.
- The computational cost and the complexity are low, when compared to SVM.

Results

Bio Medical Waste (BMW) is a waste generated from hospitals, health care institutions and medical laboratories, produced during immunization, diagnosis and treatment. The experimental results show the performance of the proposed BMW identification and classification. In this analysis, the MLTrP feature extraction method is used to histogram features of BMW image and RVM classifier is used to classify the types of wastages such as, human body parts, plastics, cotton and liquids.

Filtered Image

Initially, the BMW image is given to the input shown in Fig. 6. It contains irrelevant and highly corrupted noises, removed by using median filter. It is mainly used to eliminate salt and pepper noises from the image and the filtered image is shown in Fig. 7. The pattern of neighbors is named as window, which slides the entire image pixel by pixel. Here, the median is calculated by sorting all pixel values from the window into numerical order. Then, the pixel value is replaced as the median value (middle pixel value).

Fig. 6: Input BMW Image

Fig. 7: Filtered Image

Texture Extraction

After denoising, the texture features of the denoised image are extracted by using the MLTrP technique, shown in Fig. 8. The MLTrP illustrates the spatial structure of the local texture using the direction of the central gray pixel. The tetra pattern is calculated based on the direction of pixels using horizontal, diagonal and vertical derivatives (0°, 45° and 90°).

Confusion Matrix

Fig. 9 illustrates the confusion matrix for actual and predicted classes of BMW image. In this graph, the x-axis represents the predicted classes, y- axis represents the data samples and z-axis represents the actual classes. Confusion matrix contains information about actual and predicted classifications done by RVM classification system. The performance of this system is evaluated by using the data in the matrix.

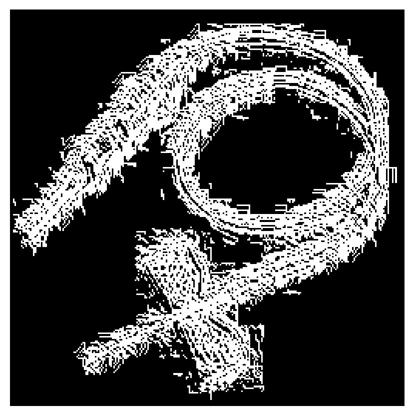

Fig. 8: Texture Feature Extraction

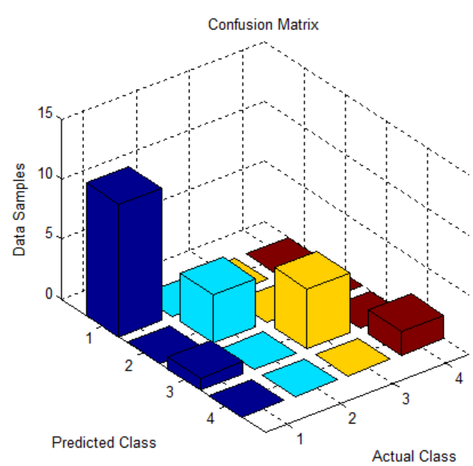

Fig. 9: Confusion Matrix for actual and predicted classes

Sensitivity and Specificity

Sensitivity is the proportion of true positives that are correctly identified by RVM classifier, expressed in percentage. Sensitivity is defined as the probability of getting a positive test result in subjects. The specificity is the number of true negative results divided by the sum of the numbers of true negative plus false positive results. The sensitivity is calculated by using,

$$Sensitivity = \frac{TP}{(TP+FN)} = \frac{Number\ of\ true\ positive\ assessments}{Number\ of\ all\ positive\ assessments} \quad [15]$$

$$Specificity = \frac{TN}{(TN+FP)} = \frac{Number\ of\ true\ negative\ assessment}{Number\ of\ all\ negative\ assessment} \quad [16]$$

The means of the formula 15 and 16 are: TP - True Positive, TN – True Negative, FP – False Positive, FN – False Negative. In this analysis, the sensitivity rate is increased by 100% and the specificity rate is increased by 91%.

Classification Rate

RVM is one of the best-known methods in pattern classification and recognition. It provides the better classification results compared with the SVM classifier. The classification rate is the perfect prediction rate increased by 100%. Error rate is the misclassification rate that reduces the performance of the classification rate, reduced by 43%. Correct rate is the accurate classification rate, increased by 95.65%. By increasing correct rate, the overall performance and the accuracy rate is also increased.

Accuracy

From this analysis, it is observed that the level of accuracy is increased by 95.65% by using the RVM classification. The results of the BMW image processing returns a result with accuracy commensurate to the sub pixel resolution, whose reproducibility can be deducted from the frequency of occurrences. Accuracy of RVM classifier can be determined from sensitivity and specificity with the presence of prevalence. The accuracy level is calculated by using,

$$Accuracy = \frac{(TN+TP)}{(TN+TP+FN+FP)} = \frac{Number\ of\ true\ correct\ assessment}{Number\ of\ all\ assessment} \quad [17]$$

Where, PL represents the positive likelihood and NL represents the negative likelihood. PL is the positive score, also termed as predictive value of a positive test result. NL is the negative score, also termed as predictive value of a negative test result.

Here, the classification accuracy of training level and training feature points is calculated for existing and proposed texture feature extraction techniques shown in Table 1. Where, $I?$ represents the noise density ratio.

$$Positive\ Likelihood\ (PL) = \frac{Sensitivity}{1-Specificity} \quad [18]$$

$$Negative\ Likelihood\ (NL) = \frac{1-Sensitivity}{Specificity} \quad [19]$$

Comparative Analysis between existing SVM and proposed RVM Classifiers

In this graph, the x-axis represents the classifiers and the y-axis represents the values of sensitivity, specificity and classification rate. From this graph, it is observed that the proposed RVM classifier provides better results, when compared with the SVM classifier. Fig. 10 shows the comparative analysis between the existing and proposed RVM classification techniques.

Table 1: Classification accuracy for existing and proposed texture feature extraction techniques (24)

Classification Accuracy Methods	ϱ = 5%	ϱ = 10%	ϱ = 20%	ϱ = 30%	ϱ = 40%
BRINT2_CS_CM (MS9)	98.63	96.55	92.64	84.54	74.26
CLBP_CS (MS9)	92.96	90.53	82.2	69.77	50.88
dis(S+M)	94.77	93.22	76.67	54.81	43.33
LTP (MS9)	92.89	91.99	86.11	77.71	64.19
NRLBP (MS9)	88.63	88.96	83.87	78.98	67.11
MLTrP (Proposed)	99.21	98.44	95.65	92.86	91.3

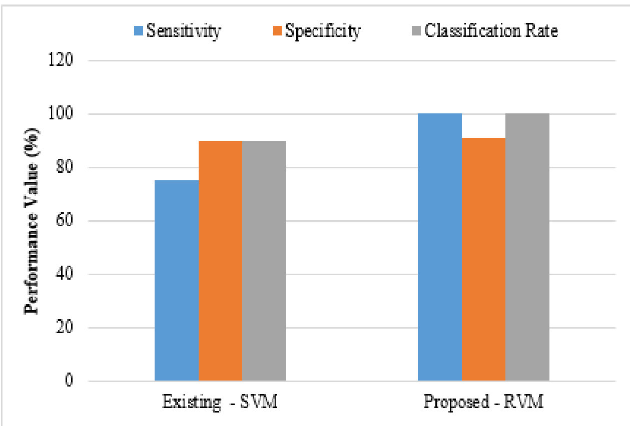

Fig. 10: Comparative analysis graph for existing SVM and proposed RVM classifiers.

Table 2: Performance Measure of RVM Classification

Performance Metrics	Value
Correct Rate	0.9565
Error Rate	0.0435
Last Correct Rate	0.9565
Last Error Rate	0.0435
Classified Rate	1
Sensitivity	1
Specificity	0.9196
Positive Predictive Value	0.9167
Negative Predictive Value	1
Positive Likelihood (PL)	12
Negative Likelihood (NL)	0
Prevalence	0.4783
Accuracy	95.6522%

Performance Measure

Table 2 shows the performance measure of RVM classification. The performance metrics such as, correct rate, error rate, sensitivity, specificity, accuracy and prevalence of the proposed BMW identification and classification system is evaluated by using the RVM classifier.

Discussion

The task has been carried out in this paper is to provide the information about the identification and classification of BMW. Several related works of BMW classification is proposed in the last decades. Classification (10) and identification of BMW is not an easy problem so, more work is needed for the task of waste stream identification. The Median Filtering technique (11-13), MLTrP (14-19) and RVM (20-23) are used to efficiently extract and verify the histogram features of BMW image. In this research, four types of wastages such as, human body parts, plastics, cottons and liquids are properly identified and classified.

In this paper, the separation of bio waste at source is concentrated. The separation of Bio Waste at source is the primary stage and recycling, reuse and recycling should be considered in appropriate perspectives. The proposed BMW identification and classification is striving toward through improving the accuracy, sensitivity, specificity and classification rate. These metrics are specifically important for BMW imaging and its becoming a predictable investigative procedure for clinical practice. In this paper, the hybrid method is developed to extract and classify the texture features of BMW image by combining MLTrP with RVM classifier. The main aim of using MLTrP technique is to extract the histogram features from the denoised BMW image. Here, the 8-bit tetra pattern and magnitude patterns are calculated based on the horizontal, diagonal and vertical directions (0°, 45° and 90°). Additionally, the RVM classification mechanism is also employed to classify accurately the waste stream into human body parts, plastics, cotton and liquids.

In future, the classification system can be improved for further systematic segregation and proper disposal of BMW.

Conclusion

BMW should be classified according to their source, type and risk factors associated with their management, handling, separation, treatment and disposal. BMW must be handled and stored in a secure environment, because it causes serious health issues to environment. In this paper, the BMW are identified and classified by using MLTrP technique and RVM classifier. Initially, the input BMW image is preprocessed by using the median filtering technique. In this stage, the irrelevant and highly corrupted noises are removed and filtered. After that, the MLTrP is used to extract the histogram features of the BMW image. Hence, the histogram pattern features are given to the input of RVM, which is a multi-class classifier mainly used for pattern classification. Finally, it classifies the BMW image into human body parts, cotton, plastics and liquid wastages.

Ethical considerations

Ethical issues (Including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, etc.) have been completely observed by the authors.

Acknowledgement

The authors declare that there is no conflict of interests.

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