

SEGREGATION OF MEDICAL WASTES USING FEEDFORWARD NEURAL NETWORKS AND IMAGE PROCESSING FOR A NEW CLASSIFICATION

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Abstract

Medical waste includes all types of waste that are produced by medical institutions, medical research centers, or laboratories. Medical waste has highly toxic substances, pathogenic viruses, and other pathogens, making it a major public health concern. Immune deficiency virus (HIV), hepatitis B virus (HBV), and some other agents related to blood diseases could be transmitted by medical waste. Thus, the study aims to develop a proper medical waste classification and its' respective colour-coding system. The effectiveness of the artificial neural network (ANN) in the recognition of image patterns of clinical wastes is also studied in this research. The existing classification system does not segregate medical waste according to its characteristics. Moreover, the same product has been divided into different categories. The pharmaceutical and cytotoxic pharmaceutical wastes are not classified as hazardous waste. The chemical, radioactive and recyclable wastes have been omitted from the classification. The current medical waste segregation method did not have separate containers for the subclasses of medical waste. By adopting these classifications and models developed in this study one can save up to 80% of their current expenditure on medical waste disposal. Further, it would reduce; cost, improper disposal, the atmospheric release of carcinogenic agents, and infection from a medical source to the wider public. Hence current developed ANN model would be further used to create an automated waste segregation instrument (named, 'AUTOM') which is commercially produced for laboratory applications and medical waste segregation.

Keywords: Artificial neural networks, Image processing, Centroidal profile, Shape recognition, Medical waste

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Introduction

Medical waste is being produced at an even more rate due to the increased use of disposable hospital devices. Although some countries, including Malaysia, recycle medical waste. Incineration remains a primary and often sole method of medical waste disposal in many countries. Incineration is recommended by the World Health Organization (WHO) as a quick and immediate alternative for developed countries (WHO, 2018).

The infectious aspect of medical waste disposal is a major concern, which makes human segregation extremely dangerous. By medical waste recycling programme, we may decrease illegal reuse and recycling (Patwary *et al.*, 2011) and there by reducing the chances of spreading infection. Many infectious waste items are mistakenly disposed of into domestic waste bags. These include sharps such as syringes and blades that can potentially cause injuries and spread diseases. Also, it is risky for incinerators and disposal equipment as they can be damaged by items that are not designed to handle (Hagen *et al.*, 2001).

A “classic” Greek landfill site is investigated by considering various options for e-waste recovery but processing goals, as well as the cost and benefits of Landfill Mining (LFM) operations. It is based on the results of the first LFM pilot project in Greece, which took place at the Polygyros landfill. The study’s findings indicate that the existence of e-waste enhances the environment. According to the findings, the inclusion of e-waste increases profitability indices. However, it appears that implementing more sophisticated recycling and recovery systems has a little financial benefit. The risk assessment performed backs up these results, revealing that the price and production of plastics are the most important variables, followed by non-ferrous metal price and its concentration. The study’s findings should be viewed with care. The financial performance of LFM ventures, however, is site-specific yet not guaranteed in all situations, as shown by international experience. As a result, it should be obvious that further study in the field is needed to address the query (Emadian *et al.*, 2017).

Healthcare facilities use a lot of dangerous and non-hazardous products and create a lot of pollution. Field experiments with ten hospitals in Brazil’s southern region revealed the lack of clear mechanisms for measuring, monitoring, improving, and reporting environmental performance in operation. The research aims to propose an alternative paradigm based on the research findings. The proposed system is operationalized using

a ‘process approach, but also its viability, usability, and usefulness are assessed (Blass *et al.*, 2017)

The research was conducted on the health hazards associated with the existing medical waste disposal in hospitals in Sana’a, Yemen. The current management of medical waste was observed and followed up through frequent visits to those studied hospitals. A preliminary risks assessment (PRA) methodology was used as an analysis tool to define and assess the possible hazards of the existing medical waste handling practices and processes in the hospitals studied. We looked at eighteen incidents including containment, segregation, processing, transportation, waste disposal, and waste management. According to the findings of this report, 89% of the incidents studied in waste handling processes were considered to be high-risk. Many of the incidents were high-risk, implying that all of these processes’ events should be prioritized. The hospital’s management and the related ministries in the government are working together to reduce or eliminate the possible risks associated with the existing handling of hospital waste (Alwabr *et al.*, 2017).

The physicochemical composition of bioplastics has a major impact on their biodegradability. However, the ecosystem in which they are found has a significant impact on their biodegradation. This analysis summarises recent studies related to bioplastic decomposition of organic matter in different habitats, environmental factors, and the degree of decomposition of organic matter, as well as the reported bioplastics (S. Mehdi *et al.*, 2017).

The use of 16S rRNA amplicon sampling to characterise microbial communities indicates which thermophilic methanogenic behavior is due to methanogens of a genus *Methanothermobacter*. This study showed that landfills can maintain active methanogenic functions even when temperatures are in the thermophilic range from a microbiological perspective (<72°C) (Florentino *et al.*, 2021).

Medical Waste Classification background

The method of medical waste classification suffers due to 90-95% of over-classification. This increases the burden of infectious waste in the facility and also the cost of disposal at the medical facilities. Hence it is aimed to develop better and new medical waste classes in the current research study.

The classification also has a new color code for appropriate segregation at the facilities. The study also aimed to develop an automated waste segregation instrument (named, ‘AUTOM’) commercially productive for laboratory applications

and medical waste recognition. It has been initiated by discovering the effectiveness of artificial neural networks in the pattern recognition of clinical waste images.

To ensure proper segregation of medical waste, it has to be automated and employed in the places where human labor is used to separate the medical wastes. Machine vision has been successfully applied in areas that were previously dominated by human workers, including assembly line verification, meat, crop, and fruit/vegetable grading, and defect detection using various methods and classification accuracies ranging from 73% to 98.8% have been reported (Chen *et al.*, 2011; Narsaiah and Jha, 2012; Patel *et al.*, 2012; Vijayarekha, 2012). Centroidal profiles and features extracted from centroidal profiles (Du *et al.*, 2007; Riyadi *et al.*, 2007) have been applied for different classifications.

The frequency of bedding, inpatient occupancy rate, number of symptoms classes, and case-mix index were all collected as part of a report. It measured the medical waste generation rate, treatment regimen group score, case-mix index score, and modified generation rate. The rate of medical waste production, diagnosis-related group ranking, case-mix index score, and modified gallons per capita are all factors to consider. The distinctions were made by grouping the participating hospitals into groups based on their degree and affiliation. While the effects of medical activities in the outpatient department on energy consumption need to be investigated further, and the application is constrained by the need for a fully configured hospital information system. With sound medical information quality control, it is still simple and performed in medical waste management of hospitals (Xin, 2015).

A growing number of studies are examining the environmental effects of medical devices and the mechanisms by which they are used from an environmental perspective. This study aimed to close these information gaps by modelling the environmental and economic impacts of medical device supply chains using life cycle assessment (LCA) and its cost assessment (LCCA) of reprocessed devices used at Phoenix Baptist Hospital (PBH) in Phoenix, Arizona. Both cradle-to-grave processes again for seven medical devices were included in the LCA. The study found that if inputs (such as ethylene oxide, water, and electricity) are optimised, reprocessed devices can reduce global warming, improve human health, and save money over disposable devices (Unger and Landis, 2016).

Mismanagement of managed waste is an expensive problem for many hospitals and care centers. The institution started a quality improvement study to determine if increasing employee awareness of scheduled waste management may help reduce surgery mismanagement. Personnel can reduce the total mass of controlled waste sampled by 41% and the total mass of nonregulated waste by 77%. Perioperative staff members are more likely to boost compliance with both the disposal of regulated waste and the disposal of hazardous waste after expanding their knowledge base, according to the audit findings. (Perrego, 2017).

The COVID-19 pandemic is already in a crucial stage of prevention and control. Since medical waste disposal is a potential source of contamination, standardisation and strict implementation of COVID-19-related medical waste management should be carefully considered to minimise the possibility of an outbreak within hospitals. This research shows how to put the theory into practice. This research shows how medical waste is handled in the event of a novel coronavirus disease outbreak in 2019-2020 (Peng *et al.*, 2020).

Materials and method

The main aim of the research was to test the effectiveness of artificial neural networks in pattern recognition of clinical waste images. The process flow comprised of several steps including image acquisition, pre-processing, and feature extraction followed by neural networks' training, testing, and validation with a new set of images.

New Medical Waste Classification and Colour code

It is critical to develop a simple classification system based on the essence of the danger presented by the object. The Malaysian Ministry of Environment guidelines, issued by the Department of Environment inspired this. (Department of Environment, Ministry of Natural Resources and Environment, Malaysia, 2009 and WHO, 2018). Table 1. Shows a proposed new medical waste classification through this study. The population's health can be ensured by designing, validating, and revising existing algorithms (Gopinath and Mohammad, 2008).

Table 1. Proposed Medical Wastes Classification and codes

No.	Class	Code	Colour code
1	Microbiological Waste	N261A	RED
2	Pathological Waste	N261B	YELLOW
3	Sharps	N261C	BLUE
4	Pharmaceutical Waste	N251D	BROWN
5	Radioactive Waste	N251E	SILVER
6	Chemical Waste	N251F	ORANGE
7	Recyclable Waste (non-infectious)	G	GREEN
8	Non-recyclable Waste (non-infectious)	H	BLACK

The new classification has been developed in such a way that it overcomes the lacuna in classification in existing methods from the UK, Europe waste code, WHO, and Malaysia.

Medical wastes, which include highly toxic chemicals, disease-causing viruses, and bacteria, will be minimised as a result of the current groups and procedures because they contain highly toxic chemicals, pathogenic viruses, and bacteria that have already been isolated (Ramani *et al.*, 2013; Gopinath *et al.*, 2017). Due to the new groups and procedures, the spread of the Human Immunodeficiency Virus (HIV), Hepatitis B Virus (HBV), and other agents related to blood diseases will be decreased.

Add to the health benefits, there are good practices in cost savings through proper waste segregation. In 2010, the University of Pittsburgh Hospital earned over \$89,000, the Good Samaritan Hospital of Suffern, New York earned over \$85,000, and the University of Maryland Medical Center in Baltimore earned over \$70,000 a year.

This paper describes the primary steps taken in developing a segregation model for medical waste items that are typically collected from hospitals and clinics using Artificial Neural Networks (ANN). A prediction model for wind energy based on Ensemble Kalman Filter (EnKF) Model for Prediction Wind Energy on Urban Building is presented in a previous study. Ensemble Kalman Filter is a powerful tool and is a recursive filter used to solve any variable problems. The EnKF technique is used to compare to Artificial Neural Network (ANN) technique. The predictive results of the prediction model and conventional ANN are compared. Finally, the experimental results show that the EnKF is a capability more than ANN (Chainok *et al.*, 2020).

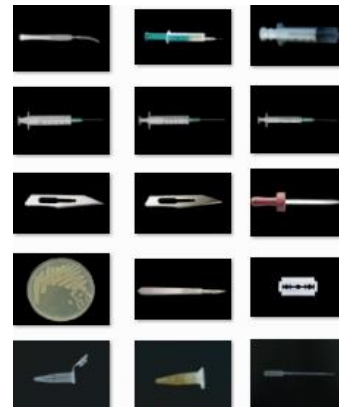
Data collection

A total of 467 photographs were obtained, and 141 of them, across 6 different subclasses, were chosen for training for this study. There were only 2 classes and 3 subclasses have been chosen to train

the network at the beginning of the study. Table 2. shows a breakdown of the number of images selected for analysis by class and subclass. A sample subset used for training has been presented in Figure 1.

Table 2. Number of training images per class/subclass

Class /Subclass	No. of medical wastes subclass used
1. Microbiological Waste (N261A)	23
Petri dishes	6
PCR tubes	9
Pipettes	8
2. Sharps (N261C)	118
Syringes	79
Scalpels	14
Blades	25

**Figure 1. A subset of our training set showing images from two classes**

During the training phase, the images used have been taken from a collection of photographs taken at the medical centers, and hospitals during data collection, and purchased medical waste images. The test images are similar to but not as same as the ones used in training. The steps are detailed in the following sections. Photographs of individual medical waste items were used to train the networks. The items were believed to be on a sorting facility's conveyor belt. The backdrop and illumination were kept steady, and the object's rotation was limited to a single plane perpendicular to the camera. Medical waste was photographed with the camera perpendicular to the object's plane, on a clean white or black plane background. This is also well demonstrated by our recent work. Camera calibration is a significant part of the accuracy of three-dimensional (3D) human motion analysis systems. Gait analysis is selected as the case study for consideration to apply a low-cost three-dimensional motion capture system to

evaluate gait characteristics. Kinovea (free and open-source) is used to retrieve the target position in two-dimensional (2D) coordinates from two cameras and the direct linear transformation (DLT) is then utilized to determine the 3D coordinates of an object using MATLAB. Statistical analysis for the study includes MAE stands for mean absolute error, RMSE stands for root mean squared error, and percent RMSE stands for percent root mean squared error was used in this study. Findings indicate that the acceptable accuracy for the low-cost gait analysis system at a 95% confidence level is between 1.13-1.36 mm. It shows that most of the MAE, RMSE, and %RMSE calibration values of 13 markers in the XY, YZ and XYZ planes are within an acceptable range (Pongmi and Yodpijit, 2021).

All objects were rotated to the same angle in the training set. Object recognition and image understanding would be performed well by artificial neural networks. ANN's performances were tested for every three steps of modeling.

Image Pre-processing

There were several image pre-processing operations carried out before the extraction of a clean outline of the item. First, the raw input image was read and converted to grayscale. The grayscale image also has its intensity values adjusted to give the best possible contrast, as shown in Figure 2. The grayscale image from Figure 2. was then converted to a binary image using thresholding levels as provided by MATLAB's Image Processing' function, which uses Otsu's method to determine a suitable threshold. A hole filling operation was applied to the binary image to rid it of any enclosed holes.

Figure 3. shows the binarised image which has most of the letters and graduation marks on the syringe has already been removed. Some letters and graduation marks remain as it was not made up of enclosed holes in the body. These could be removed or at least smoothed over by dilating and eroding the image. Two structuring elements namely horizontal and vertical lines of length equal to 7 pixels were used for both operations. Figure 4. (left) shows the dilated image where most of the irregularities on the edge have been smoothed over. The dilated image was then eroded using the same structuring elements to bring the shape back to its original size. It also highlights unwanted noise. This was removed by a morphological opening function that removes objects with an area less than that was specified.

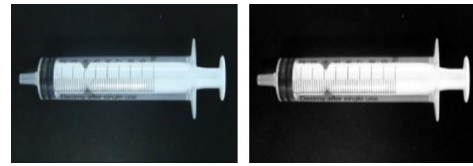


Figure 2. Input image (left) and Grayscale and intensity adjusted image (right)

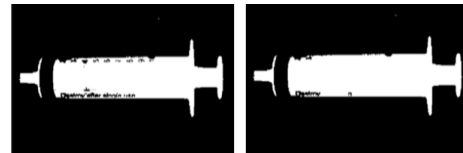


Figure 3. Binary image (left) and Binary image with filled holes (right)



Figure 4. (left) Dilated binary image, (right) Eroded binary image after a dilation

Image processing for Centroidal Profile extraction

The shape description, namely, the centroidal profile has been tested and plotted typically as the distance from the centroid Vs. the angle. In the case of non-star-shaped objects, plotting the profile against angle does not result in a one-dimensional array. Hence it was decided to calculate the distance of each pixel in a traced boundary instead. This has resulted in a one-dimensional array of lengths equal to that of the extracted boundary.

The image obtained was used as the input to a boundary tracing function (bwtraceboundary) from Matlab's image processing toolbox. The function followed the boundary of the blob in the clockwise direction and its output is an array of the path followed. The centroid was obtained using the region props function from Matlab's image processing toolbox. For objects with more than one blob, the centroidal profiles were appended onto the main array. As most of these objects were currently of simple shapes, it had not made a large difference. The approach was improved in the next modeling in the study.

Using the distance formula, the distance of the centroid from each point in the boundary array was calculated. The result was a 150-element array

containing the distances of each point from the centroid. Figure 5. shows the traced boundary of the main body of the syringe and its centroid. The array in this figure was normalised to a length of 100 elements and a maximum value of 10. It also shows the centroidal profile array calculated by measuring the distance between the centroid and each point in the centroidal profile array.

Figure 6. shows the centroidal profiles of a few common clinical waste items used in this training set. Thus, the main advantage of the centroidal profile approach is that objects can be rotated by simply rotating the one-dimensional array, all orientations can be quickly tested during testing.

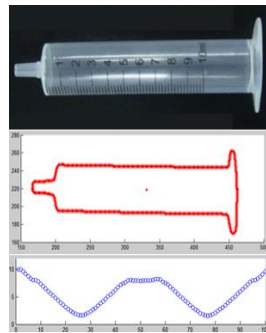


Figure 5. (top to bottom) A syringe, its boundary and centroid, and its extracted centroidal profile

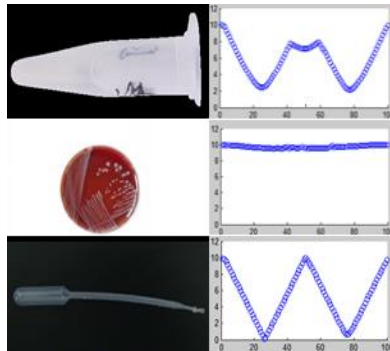


Figure 6. (top to bottom) Images and centroidal profiles of a PCR tube, a Petri dish, and a disposable pipette

Normalization

The data used in the research analysis is shown in Table 3. The length of all extracted centroidal profiles was normalised to 150 elements using MATLAB's built-in interp1 function because size invariance was chosen for this analysis. The length of the chain code is correlated to the perimeter (in pixels) of the target, which does not always represent its actual size.

Table 3. Default training and preprocessing parameters

Parameter	Value
Network Type	Pattern Matching
Hidden Layers	1
Neurons	[30] neurons
Training algorithm	[various]
Input size	150 elements
Input functions	disabled

Artificial Neural Network Training

Feedforward neural networks were trained using the extracted features with a variety of backpropagation algorithms.

System Specifications

Both operations were carried out on a 64-bit Windows 7 version of MATLAB 2012a. The program was run on a computer with a 2.50GHz Intel Core i7 2860QM processor and 32GB with DDR3 RAM. The input function row referred to the default input function as applied to all inputs (MATLAB's neural network toolbox) as listed in Table 4.

Table 4. Training algorithms and their respective function names

Training method	Function name
Bayesian Regulation	trainbr
Levenberg Marquadt	trainlm
Resilient Backprop.	trainrp
Conjugate gradient w/Polak Ribiere restarts	traincgp
Conjugate gradient w/Beale Powell restarts	traincgb
Scaled conjugate gradient	trainscg
One Step Secant	trainoss

Training set

The training set consisted of 141 images that have to be classified into 6 new classes as listed in Table1. The sample length was set to 150 elements. Each input formed the basis of 25 "virtual samples" with random noise added to individual elements. Thus, multiplying the total input sample count by 26, gave 3666 inputs. Each sample corresponded to one column in the input matrix yielded an input matrix with 150 rows and 3666 columns. Figure 7. shows how the inputs are prepared and structured as a single matrix before being used as inputs to train and test the networks.

After the centroidal profile matrix has been prepared, a random value between +0.5 and -0.5 was added to each element in each column, and the new column was added after the original. This was repeated 25 times for each input, resulting in 26 samples derived from a single image.

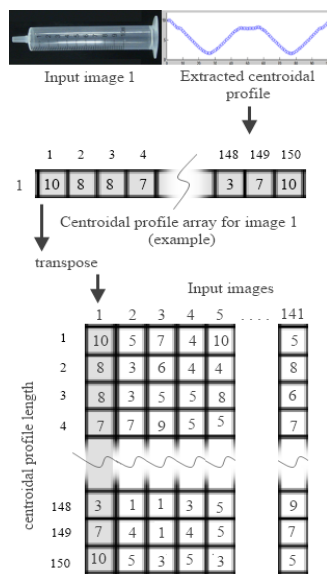


Figure 7. Structuring the training set into a format suitable for neural network input

The network was trained twice for each training algorithm.

1. First set: The network was trained and tested with the full set of images. This tests how well the networks could be trained.

2. Second set: This set was trained with 40% (1,466 samples) of the inputs, and then tested with the remaining 60% (2,200 samples) of inputs, which were never seen by the network during training (apart from a few similar noisy samples). The input samples of each class were divided into this ratio and not the entire input matrix.

These functions removed constant rows and zero elements, which was undesirable for this application.

Figure 8. shows a sample output from network training for the classification of 6 classes. Input 1 and 2 were syringes, 3 and 4 were scalpels, 5 was a Petri dish and 141 was a pipette.

The training algorithms were tested, and their corresponding function in MATLAB's Artificial Neural Networks have been used. These names have been used to refer to their respective algorithms from this point onwards. An ideal ANN output for the second set of images has been shown in Figure 9. In both sets, the ratio of the number of inputs per class remained the same.

Classification

To improve the network's recognition efficiency, the training set for one class was compared to images from other classes. After the neural network has identified the object, it will be classified based on the pre-determined

classification system as listed in Table 1. Some objects may belong to more than one class, and the differences were not always visible. In this case, the system would look at other objects that might have been identified before making a final decision about their classification.

	1	2	3	4	5	...	141
Petridishes	0	0	0	0	1		0
PCR tubes	0	0	0	0	0		0
Pipettes	0	0	0	0	0		1
Syringes	1	1	0	0	0		0
Scalpels	0	0	1	1	0		0
Blades	0	0	0	0	0		0

Figure 8. Sample ANN training output

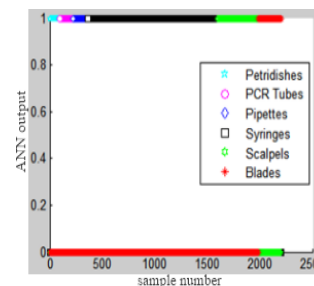


Figure 9. ANN training output of the Second set

Results and Discussion

Training and testing ANN with centroidal profiles showed better promising results than ANN alone. The hybrid ANN with image processing was robust in identifying even small variations amongst similar shapes of medical waste images presented to the network. The networks were trained using the algorithms listed in Table 4.

Training sets

The network has a single hidden layer of 30 neurons and was trained using several algorithms as listed in Table 1. The networks were trained several times for each case, and only the best-trained networks have been presented here.

The first set (all images)

The training performance results are presented in Figure 10 and Figure 11. The network has failed to train thoroughly using resilient backpropagation, which classified all inputs as class 3. Training using the one-step secant algorithm was also not entirely successful. However, other methods gave a reasonable and useable result. Figure 10 and Figure 11. showed the recollection performances of

networks trained with trainbr and trainlm respectively.

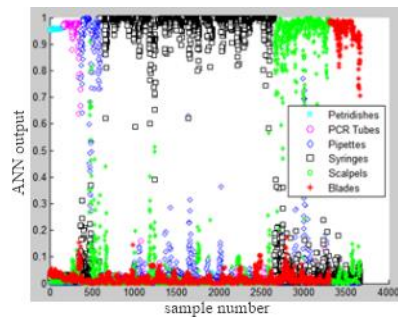


Figure 10. Recollection performance for a network trained with trainbr

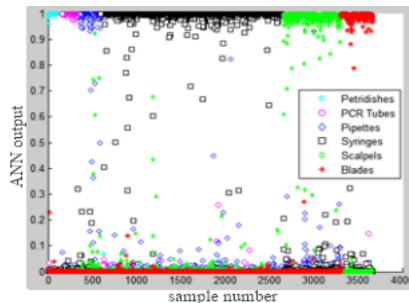


Figure 11. Recollection performance for a network trained with trainlm

Although the number of inputs correctly recalled, was slightly higher in the first network and the separation between the different classes was better with the time in seconds. The space in the Centre of the plot shows that most of the output columns have an element near the top and the other 5 elements near the bottom. This was closer to the ideal outputs as described in Table 5. Other training methods have offered better recollection in a supposedly shorter time. However, they have to be trained several times before a good result could be obtained. The trainbr and trainlm algorithms were more reliable and provided better results on average values.

Table 5. Training performance and network recollection results

Training method	Best Perf. (mse)	Training time (s)	% correctly recalled
trainbr	1.4E-03	27092s	99.95%
trainlm	4.0E-08	215s	99.78%
trainrp	1.1E-01	2s	56.03%
traincgp	1.5E-06	89s	99.92%
traincgb	1.2E-06	81s	99.97%
trainscg	1.1E-06	98s	99.92%
trainoss	7.2E-02	101s	71.46%

Second set

The training and testing performed for the second set of inputs consisting of 60% for training and 40% for testing were chosen. The results are presented in Table 6. The networks trained with trainbr, trainlm, traincgp, and training also offered good separation performances as shown in Figure 12, Figure 13, Figure 14 and Figure 15. The best recognition performance (rated by the number of inputs correctly classified) was presented by the Levenberg-Marquardt algorithm, followed closely by the Scaled Conjugate Gradient, Bayesian Regulation and Polak Ribiere restart algorithms. Bayesian Regulation and Levenberg-Marquardt algorithms were still preferred as they could be trained more reliably than other methods.

Table 6. Training performance with the second set of inputs

Training method	Best Perf. (mse)	Training time (s)	% correctly recognised
trainbr	4.57E-08	639s	81.47%
trainlm	8.24E-08	83s	83.29%
trainrp	1.06E-02	1s\	55.99%
traincgp	1.37E-04	27s	81.15%
traincgb	1.31E-06	51s	75.80%
trainscg	3.63E-08	33s	81.83%
trainoss	1.65E-02	89s	70.62%

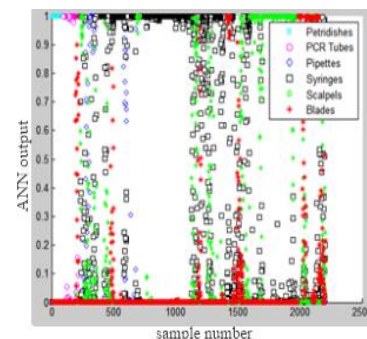


Figure 12. The second set of Network trained with trainbr

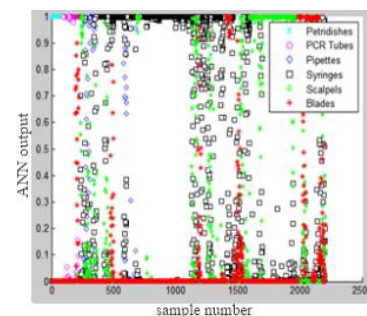


Figure 13. The second set of a network trained with trainlm

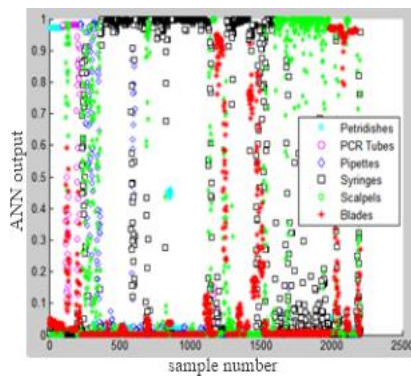


Figure 14. The second set of a network trained with **traincgp**

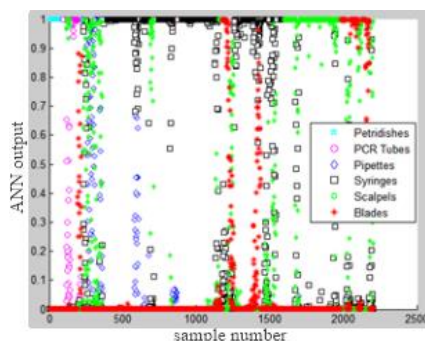


Figure 15. The second set of a network trained with **trainscg**

They usually gave a better separation between the classes in the output vector than other methods. But training had to be performed several times before obtaining an acceptable accuracy. Anyway, some training methods resulted in networks with accuracy as low as 63% while the lowest accuracy obtained using the **trainlm** and **trainbr** methods were 74%. The columns with greater percentages represent objects with similar shapes which has raised the values of the output vector elements in more than one class.

Conclusions

A study on different Feedforward training methods for the classification of medical wastes has been presented in this paper. The pre-processing and centroidal profile extraction routines provided consistent and usable features, and training and network performance are found to be consistent using the images in this training. It is also found that the performance could be improved with more images and classes to the training set. From this research study, it is found that the Levenberg-

Marquardt algorithm classifies the objects in this training set with approximately 83%, and testing is used to give an accuracy value between 75-83%. Thus, it is to provide a waste segregation system that also comprises a newly developed classification of medical wastes. The present invention provides a waste segregation system to segregate wastes with the integration of a neural network, field programmable grey array (FPGA), and centroidal profile or texture. It provides an efficient and cost-effective waste segregation system, which contributes to a reduction of environmental pollution.

The current model could be extended to additional classes by adding to the image pool, the training networks with multiple hidden layers, and an increased number of neurons. Further, a texture classification method can provide a few additional parameters to classify an object. Adopting the proper classification and segregation model established in this study for medical waste would minimise the cost of disposal, unsafe disposals, and the release of carcinogenic agents into the atmosphere, and the transmission of infection from a hospital environment to the public.

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