Automatic Dry Waste Classification for Recycling Purpose

Muhammad Nuzul Naim Baharuddin, Hassan Mehmood Khan, Norrima Mokhtar*, Wan Amirul Wan Mahiyiddin
Department of Electrical Engineering, Faculty of Engineering, University of Malaya, Malaysia

Heshalini Rajagopal
Department of Electrical and Electronic Engineering, Manipal International University, Malaysia

Tarmizi Adam
Faculty of Engineering, School of Computing, Universiti Teknologi Malaysia 81310 Johor Bahru, Johor, Malaysia

Jafferi Jamaluddin
UM Power Energy Dedicated Advanced Centre, Universiti Malaya, 50603, Kuala Lumpur Malaysia

E-mail: nuzulnaim140297@gmail.comnorrimamokhtar@um.edu.my, heshalini@gmail.com

Abstract

There has been a serious increment in solid waste in the past decades due to rapid urbanization and industrialization. Therefore, it becomes a big issue and challenges which need to have a great concern, as accumulation of solid waste would result in environmental pollution. Recycling is a method which has been prominent in order to deal with the problems, as it is assumed to be economically and environmentally beneficial. It is important to have a wide number of intelligent waste management system and several methods to overcome this challenge. This paper explores the application of image processing techniques in recyclable variety type of dry waste. An automated vision-based recognition system is modelled on image analysis which involves image acquisition, feature extraction, and classification. In this study, an intelligent waste material classification system is proposed to extract 11 features from each dry waste image. There are 4 classifiers, Quadratic Support Vector Machine, Cubic Support Vector Machine, Fine K-Nearest Neighbor and Weighted K-Nearest Neighbor, were used to classify the waste into different type such as bottle, box, crumble, flat, cup, food container and tin. A Cubic Support Vector Machine (C-SVM) classifier led to promising results with accuracy of training and testing, 83.3% and 81.43%, respectively. The performance of C-SVM classifier is considerably good which provides consistent performance and faster computation time. Further classification process is improved by utilization of Speeded-Up Robust Features (SURF) method with some limitations such as longer response and computation time.

Keywords: Support Vector Machine, Recycling, Feature Extraction, Classification.

1. Introduction

Solid wastes refer here to all non-liquid wastes. In general, this does not include excreta, although sometimes nappies and the faeces of young children may be mixed with solid waste. Solid waste can create significant health problems and a very unpleasant living environment if not disposed of safely and appropriately. If not correctly disposed of, waster may provide breeding sites for insect vectors, pests, snakes and vermin (rats) that can increase the likelihood of disease transmission. It may also pollute water sources and the environment. This is why solid wastes are known as the most critical problems of our time. There is no place in the corner of the earth that currently immune from the municipal solid waste. The statistics show that, since the beginning of last decade, an increasing sharply amount of solid wastes has been generated[1]. A large quantity of solid waste production is correlated with the GDP. High GDP tends to produce large quantity of solid waste. Updated report data are shown by the world bank report that there are about 4 billion tons of waste generated every year globally which urban area is one of the main contributors to the huge numbers and the waste is estimated to be up until 70% by 2025. In the next 25 years, number of wastes accumulated will be rapidly increased in underdeveloped nations due to accelerated pace of urbanization and industrialization [2].

The population growth rate has continued of 2.4% per year since 1994 based on Department of Statistic Malaysia in 2012. The higher the growing number of people with higher consumption rates, the higher the amount of waste generation. There is a correlation between the income rate and urbanization. As the disposable income and living standard increase, the consumption of products and services, as well as the quantity of waste produces rise correspondingly. With an incrementing number of industries in the urban area, thus, solid waste management becomes a critical concern and challenging for municipal authorities worldwide since the drastically amount of waste generated. Solid waste management confronts more complex problems in the developing nations due to limited door-to-door collection, inefficient treatment and inadequate disposal facilities [3]. Majority of the solid waste is comprised of waste that mainly found in public which consists of paper, plastics, and glass waste material.

The main method to manage waste is landfilling. In U.S.A, 80% of the trash is managed by landfilling which present serious health and ecological problems. This is why landfilling is inefficient since its high-cost operation and most important, polluting the environment. For instance, people who stay around at landfill site can affect their own health. Another solution to manage waste by reducing the volume of the waste is burning waste in Incinerators. However, this method more driven to negative effects, caused severe health problems such as cancer due to human exposure to polycyclic aromatic hydrocarbons (PAHs), which is hazardous and might spread into the air during the air pollution. This method costs a lot of money to be invested in order to build, operate and maintain the machine. Today, the most effective in solving waste disposal problems is recycling and reusing. Based on recent research data, the amount summed up is about 150 million tons. Solid waste is often rich source of various recyclable materials. According to Gundupalli et al. (2017), these recyclable materials can be recovered, become useful and reduce the negative impact on the environment. Waste sorting practices on the other hand, is a beginning step in solid waste management for the recycling of materials. This waste sorting technique is implemented in order for the separation of waste into their different categorization component which can be recycled using different techniques. Hence, recycling is an important tool to assure that our environment is protected as well as human's health [2].

Many studies have been conducted and there are a lot of research papers published in the area of waste sorting and classification using different methods. The main focus in this study is automated sorting of dry wastes such as plastic, bottle, paper and tin cans by means of classification and vision system. Thus, we study literature by the types of materials classified and techniques used for sorting multi-material classification. This contributes to the motivation of this work which are to improve the lacking of prominent, outstanding and discriminative features for excellent classification accuracy.

2. Methods

2.1 Vision-based recognition system

The proposed dry waste classification system by using vision inspection method consists of several module: image acquisition, image processing, feature extraction, classification and finally determined the decision as shown in Fig. 1.

2.2 Image Acquisition

Image acquisition always be the first step when involving image processing. Fig. 2 shows the inspection zone of the waste sorting system which have been covered with housing made up of box where the images were taken for classification later. RGB images are manually taken using a web camera (Logitech QuickCam V-UAP41 USB) within the inspection zone. The camera was attached on top-middle surface of the box after the box is upside down. The setup distance between the camera and the test sample is secured at 25 cm. All the properties setting such as the brightness, contrast and saturation are adjusted based on their respective scales. For the illumination technique, homogenous lighting is adopted for this experiment to obtain a set of geometric properties. This can be done by having the size, shape, orientation and position of the waste samples.

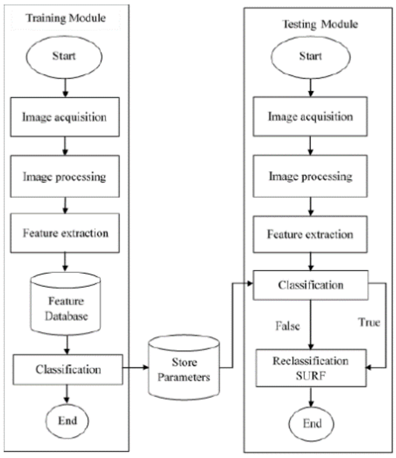


Fig. 1. Conceptual framework for training and testing stage proposed by the system.

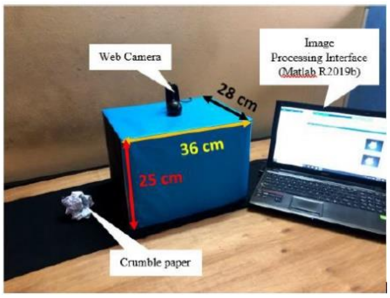


Fig. 2. A photographic image of a setup for vision-based recognition system.

In this experiment, 210 samples are used for training purpose while 70 samples are collected from different place of trash bins such as homes, offices, shops and markets. The test samples consist of 7 different type of class which are 10 test samples of crumble garbage, 10 test samples of flat garbage, 10 test samples of tin cans, 10 test samples of bottles, 10 test samples of food container, 10 test samples of cup and 10 test samples of box. For example, Fig. 3 shows a set of test sample that were randomly picked from each of the class. All the test samples have different looks; shape, size, diameter and orientation. The resolution of each captured photograph is 640×480 pixels.

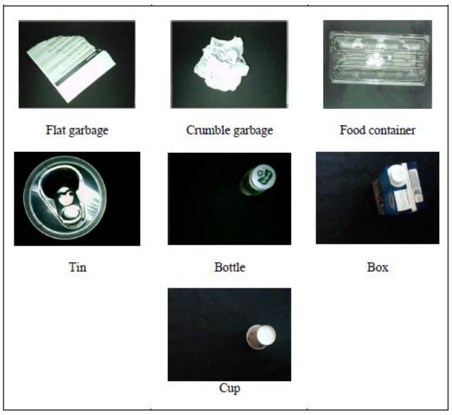
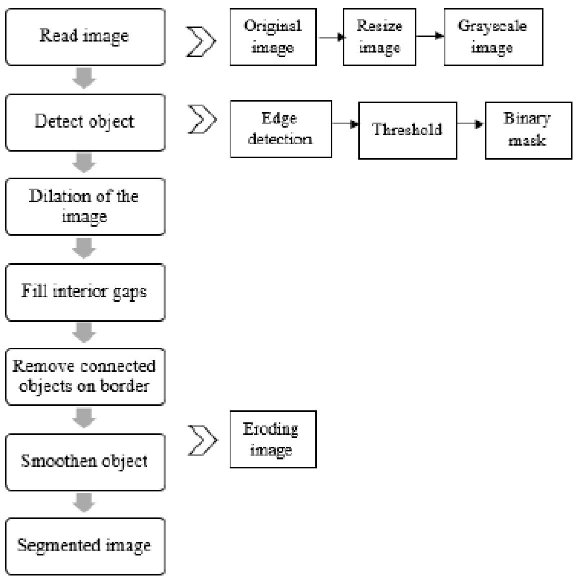


Fig.3. Representative image of dry waste samples.

2.3 Image Processing

In this section, image pre-processing technique such as segmentation or thresholding is discussed. The basic idea of image segmentation is to extract the area of effect of the test sample. Hence, object detection is a starter pack module in this part. There are many techniques developed to find an object from an image, such as object detection algorithm to extract objects in 2-D intensity images using boasted cascade [4], histogram of gradient [5], shift invariant feature transform [6], its background. Segmentation flow of the processing sample image are illustrated in Fig. 4. From Fig. 4, an original image with size 640×480 pixels, is read into the system by using MATLAB R2019b. This RGB sample image is resized to 320×240 pixels by factor of 0.5. This true colour RGB image is converted to greyscale format, where an integer value between 0 to 255, in order to reduce the complexity since RGB image is 3 dimensions and grayscale image is of only 2 dimensions. In order to detect the entire area of the sample image, the background information of the images was eliminated using edge detection and morphological operations. The difference or change in contrast between the object's image and background can be detected by operators. This is done by performing a calculation of the gradient of an image. In this experimental study, a fudge factor value is set to 0.9. The edge detector used in this experimental study is Sobel filter, which is suitable for this condition as Sobel operator more sensitive to diagonal edge than horizontal and vertical edges. Edge detection was performed so that the resulting outline of the images are very precisely. Sobel operator also is used to calculate the threshold values, and edge detection to get the binary mask. The outline images were dilated using linear structure elements to produce more accurate gradient mask. The holes in the dilated images were filled up using morphological operations to fill gaps in images at unfilled area. The cell of interest has been successfully segmented, but it is not the only object that has been found. Any objects that are connected to the border of the image can be removed. Basically, the edge detection and morphological operations are done to perform the segmentation of the samples from the background. Therefore, the area of crumble garbage is extracted by using the mentioned morphological operators. Segmentation flow process for each type of class samples is shown in Fig. 5.



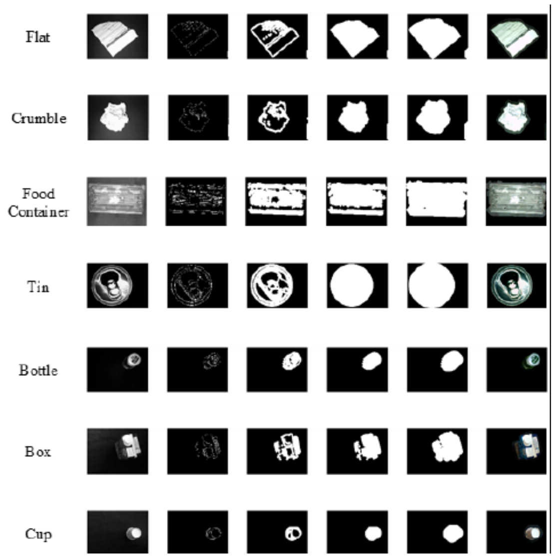


Fig. 4. Flowchart of the sample image in image processing

Fig. 5. The segmentation steps of processing dry waste sample images

2.4 Feature Extraction

Features are used to build classifier model in order to determine the material type and location or coordinates. The feature extraction from the test samples was done using image processing. The operational flow on the test samples for image segmentation is shown in Fig. 6. There are 2 different datasets proposed in this experimental study; the first dataset was extracted from white pixel plot of the sample and the second dataset was extracted from segmented grey image of the sample. Two datasets for training and testing are created by combining statistical and non-statistical features. The dataset is extracted from segmented grey image and white column matrix. From segmented grey image, features such as grey level co-occurrence matrix (GLCM), ratio of grey level, entropy and standard deviation are extracted. This feature dataset is also extracted from the plot of binary mask images of the sample. The white pixel plot of each sample images has different shape which made it possible to extract features for classification. The statistical data applied from the white pixel plot is quantile. The GLCM depicts second order statistical analysis of an image by analyzing how often the pairs of pixels which consist of specific values and spatial relationship take place in an image. The probability, $p(m,n)$ is computed using Eq. (1) [7]:

$$p(m,n) = \{C(m,n)|(d,\theta)\} \quad (1)$$

where d is the inter-pixels displacement distance, θ denotes orientation and $C(m,n)$ denotes the frequency of gray level occurrence in MSCN of the image. Four statistical textures such as contrast, correlation, energy, and homogeneity were extracted from the GLCM matrix.

Contrast calculates the local variations in the gray-level co-occurrence matrix and is defined as Eq. (2) [7]:

$$\text{Contrast} = \sum_{m,n} |m-n|^2 p(m,n) \quad (2)$$

Correlation computes the joint probability occurrence of the specified pixel pairs and is defined as Eq. (3) [7]:

$$\text{Correlation} = \sum_{m,n} \frac{(m-\mu m)(n-\mu n)p(m,n)}{\sigma_m \sigma_n} \quad (3)$$

Energy calculates the sum of squared components in the GLCM. It is also known as uniformity or the angular second moment. The energy parameter is computed as Eq. (4) [7]:

$$\text{Energy} = \sum_{m,n} p(m,n)^2 \quad (4)$$

Homogeneity calculates the closeness of the distribution of elements in the GLCM to the GLCM

diagonal and is computed as Eq. (5) [7]:

$$\text{Homogeneity} = \sum_{m,n} \frac{p(m,n)}{1+|m-n|} \quad (5)$$

Fig. 6. Summary of image processing used in this experimental study

Grey level is fundamental in study of image processing. The grey level or grey value indicates the brightness of a pixel. The maximum grey value depends on the depth of an image. For example, 8-bit-deep image contain levels up to 255, which they can take any value in the range. However, binary image can only take either value 0 or 255. Table 1 shows the summary of grey level. The program has been setup to calculate ratio of grey level (L) and ratio of grey level (H). Here, ratio of grey level (H) is denote as $40 < x \leq 110$, and ratio of grey level (L) is denote as $181 \leq x \leq 255$.

Grey level	Colour
0	Black
0 < x < 255	Grey
255	White

Table 1. Grey level and its respective color

In image processing, entropy is a statistical measure of randomness that can be used to characterize the texture of the input image [8]. The higher the value of entropy will result as the more detailed information of an image. Entropy is a measure image information content, which is interpreted as the average uncertainty of information source. A vector with relatively "low" entropy is a vector with relatively low information content, such as it might be [0 1 0 1 1 1 0]. A vector with relatively "high" entropy is a vector with relatively high information content such as it might be [0 242 124 222 149 13]. Hence, it is very important to have higher entropy in order to have precise segmented image after image post-processing method so that it can classify accordingly to its own type of groups. Entropy algorithm is shown in Eq. (6):

$$\mu_m = \sum_{m,n=0}^{i-1} p_{m,n}\left(-\ln\left(p_{m,n}\right)\right) \quad (6)$$

Standard deviation is a most common method used to calculate variability or diversity in statistic. In image processing, it shows how much discrepancy, or "dispersion" exists from the mean value. Total standard deviation used as a more accurate expression of the statistical distribution of each class [9].

Maximum quantile finds the quantities between the data values using linear interpolation which using linear. Initially, quantile assigns the sorted values in x to the (0.5/n), …., ([n-0.5]/n) quantiles [10].

2.5 Classification

2.5.1 Support Vector Machine (SVM)

The classification process SVM in the experiment is carried out by using Classifier Learner Application in MATLAB [11]. There are about six classification models under category SVM, which are linear SVM, quadratic SVM, cubic SVM, fine gaussian SVM, medium gaussian SVM and coarse gaussian SVM. Experiment using the 5-fold cross-validation is applied to evaluate the prediction accuracy of the model, which optimum number of k-fold applied is 5. If the number of k-fold increase, it will result in lower accuracy. In contrast, the accuracy will increase but it does not protect from the overfitting data. Cost matrix applied in this experiment are using default setting for misclassification costs. Other parameters used for the SVM is shown in Table 2.

Table 2. Parameters setting for SVM using classifier learner application

Type of SVM	Parameters			
	Kernel scale	Box constraint	Multiclass method	Standardized data
Linear	Automatic	1	One-vs-One	True
Quadratic	Automatic	1	One-vs-One	True
Cubic	Automatic	1	One-vs-One	True
Fine Gaussian	0.79	1	One-vs-One	True
Medium Gaussian	3.2	1	One-vs-One	True
Coarse Gaussian	13	1	One-vs-One	True

2.5.2 K-Nearest Neighbor

The training examples are vectors in a multidimensional feature space, each with a class label. The training phase of the algorithm consists only of storing the feature vectors and class labels of the training samples. k is a user-defined constant at the classification stage, and a non-labelled vector (a query or test point) is classified by allocating the tag that is the one most common in the k training datasets closest to that query point. The Euclidian distance is a popular distance metric for sustained variables, for which a different metric may be used, such as a differentiation metric (or Hamming distance) for discrete variables such as text classification. In the context of micro-array data on gene expression, k-NN for example was used as metric for coefficients such as Pearson and Spearman. Often, if a distance metric is learned with special algorithms, such as Large Margin Nearest Neighbor and Neighborhood components, the grading accuracy of k-NNN can significantly be enhanced. When the class allocation is skewed, there is a drawback in the fundamental "majority voting" classification. That is, examples of a more regular class tend to dominate the new example prediction because they are common among k neighbors, because they are numerous. One way to overcome this problem is by assessing the distance between the test point and each of its closest neighbors. Each of the nearest k points is multiplied by a 35 weight proportional to the opposite distance of that point to the test point by a class (or value, in regression problems). The parameters used for the KNN is shown in Table 3. Cost matrix applied in this experiment are using default setting for misclassification costs.

Table 3. Parameters setting for KNN using classifier learner application

Type of KNN	Parameters			
	Number of neighbor	Distance metric	Distance weight	Standardized data
Fine	1	Euclidean	Equal	True
Medium	10	Euclidean	Equal	True
Coarse	100	Euclidean	Equal	True
Cosine	10	Cosine	Equal	True
Cubic	10	Cubic	Equal	True
Weighted	13	Euclidean	Squared Inverse	True

3. Results and Discussions

3.1 Preparing training, validation and testing sets

In this experiment, seven type of dry waste are used, which are bottle, box, crumble garbage, flat garbage, cup, food container and tin cans. For each of the class, 30 images of the samples were collected. The experiments were carried out in two stages: training phase and testing phase. Table 4 shows the dataset of dry waste images.

Table 4: Dataset of dry waste images.

Type of dry wastes	Number of training samples	Number of testing samples
Bottle	30	10
Box	30	10
Crumble garbage	30	10
Flat garbage	30	10
Cup	30	10
Food container	30	10
Tin can	30	10
Total	**210**	**70**

3.2 Training Results

Table 5 shows the training results obtained by 4 classifiers used in this experiment. Table 6 shows the average classification accuracy for each classifier. From the experiment that has been conducted, all of the classifier were trained as the predictive model for validation purpose.

Table 5. Training classification accuracy results

Classifier	Number of training									
	1	2	3	4	5	6	7	8	9	10
Quadratic SVM	80	79	76.7	77.1	79	75.7	79	73.3	78.6	75.7
Cubic SVM	83.3	81.9	81	80	82.4	79.5	80	78.1	81	80.5
Fine KNN	81.4	83.8	82.4	81.9	84.8	80.5	83.3	81	82.4	81.9
Weighted KNN	81.4	83.8	82.4	81.9	84.8	80.5	83.3	81	82.4	81.9

Table 6. Average training accuracy

Classifier	Average training accuracy (%)
Quadratic SVM	77.41
Cubic SVM	80.77
Fine KNN	82.34
Weighted KNN	79.62

3.2 Testing Results

Table 7 shows the testing classification accuracy for each classifier. Noted that "Models" column in Table 7 refers to the best classification models which are been saved up as predictive models used for testing experiment.

Table 7. Training classification accuracy result

Type of classifier	Models (training session)	Number of testing sample predicted correctly	Classification accuracy (%)
Quadratic SVM	1	52	74.29
Cubic SVM	1	57	81.43
Fine KNN	5	45	64.29
Weighted KNN	9	44	62.86

From Table 7, it can be seen that Cubic SVM has the highest classification accuracy for testing phase with 81.43%, even though Fine KNN have the highest training accuracy with 82.34%, but the results for classification accuracy during testing phase for Fine KNN is much lower.

4 Conclusion

In this research study, types of dry waste recognition for recycling purpose by using image processing based on some features extraction and image pre-processing approaches is submitted. 7 types of dry waste (bottle, box, crumble garbage, flat garbage, tin can, food container and cup) have being success to recognize. Image pre-processing approaches such as edge detection, image dilating, image filling and image smoothing were able to be applied in order, to differentiate all those types of dry wastes into 7 different classes.

White pixel plot also played important role in separated all those data in the beginning so that a clear picture of each class can be differentiate earlier. Then, other approaches help in recognizing each type of dry waste based on load sample image.

References

1. Guerrero L A, Maas G, Hogland W. Solid Waste Management Challenges For Cities In Developing Countries[J]. Waste Management, 2013, 33(1): 220–232. DOI:10.1016/J.Wasman.2012.09.008.
2. Adedeji O, Wang Z. Intelligent Waste Classification System Using Deep Learning Convolutional Neural Network[J/Ol]. Procedia Manufacturing, 2019, 35: 607–612. Doi:10.1016/J.Promfg.2019.05.086.
3. Gundupalli S P, Hait S, Thakur A. A Review On Automated Sorting Of Source-Separated Municipal Solid Waste For Recycling[J]. Waste Management, 2017,60:56–74. DOI:10.1016/J.Wasman.2016.09.015.
4. Viola P, Jones M. Rapid Object Detection Using A Boosted Cascade Of Simple Features[C]//Proceedings Of The 2001 Ieee Computer Society Conference On Computer Vision And Pattern Recognition. CVPR 2001. Ieee Comput. Soc, 2001: I-511-I–518. DOI:10.1109/Cvpr.2001.990517.
5. Dalal N, Triggs B. Histograms Of Oriented Gradients For Human Detection[C]//2005 Ieee Computer Society Conference On Computer Vision And Pattern Recognition (CVPR'05). Ieee, 2005: 886–893. DOI:10.1109/Cvpr.2005.177.
6. Lowe D G. Distinctive Image Features From Scale-Invariant Keypoints[J]. International Journal Of Computer Vision, 2004, 60(2): 91–110. DOI:10.1023/B:Visi.0000029664.99615.94.
7. Abd Latif, Mh, Md. Yusof, H, Sidek, S.N, Rusli N. Implementation Of GLCM Features In Thermal Imaging Affective State Detection[C]//IEEE International Symposium On Robotics And Intelligent Sensors. . DOI:10.1016/J.Procs.2015.12.298.
8. Mente, Rajivkumar, B. V. Dhandra And G M. Image Recognition Using Texture And Color[J]. International Journal Of Computer Applications, 2014: 33–35.
9. Mario Mastriani A E G. Enhanced Directional Smoothing Algorithm For Edge-Preserving Smoothing Of Synthetic-Aperture Radar Images[J]. Journal Of Measurement Science Review, 2004, 4(3): 1–11.
10. Langford E. Quartiles In Elementary Statistics[J]. Journal Of Statistics Education, 2006, 14(3). DOI:10.1080/10691898.2006.11910589.
11. Chang, Chih-Chung And Lin C-J. Libsvm: A Library For Support Vector Machines[J]. Acm Transactions On Intelligent Systems And Technology, 2011, 2(3): 27:1--27:27.

Authors Introduction

Mr. Muhammad Nuzul Naim Baharuddin

He received his B.E (Electrical) in 2020 from University of Malaya, Malaysia. Currently, he is attached to Department of Statistics Malaysia. His research interest includes image processing, artificial intelligence and machine learning.

Mr. Hassan Mehmood Khan

He received his B.E in Electronics from Dawood University of Engineering and Technology, Pakistan in 2009. He is currently submitted his Master of Engineering Science with University of Malaya, Malaysia. From 2015 to 2020, he has been as Head of Department(Mechatronics) at MIT Academy Sdn. Bhd. His research interests include automation, image processing, machine learning, and artificial intelligence.

Dr. Norrima Mokhtar

She received the B.Eng. degree from University of Malaya, the M.Eng. and the Ph.D. degree from Oita Univerity, Japan. She is currently a senior lecturer in the Department of Electrical Engineering, University of Malaya. Her research interests are signal processing and human machine interface.

Dr. Heshalini Rajagopal

She received her PhD from University of Malaya, Malaysia in 2021. She received the B.E (Electrical) in 2013 and MEngSc in 2016 from University of Malaya, Malaysia. Currently, she is a lecturer in Manipal International University, Nilai, Malaysia. Her research interest include image processing, artificial intelligence and machine learning.

Dr. Tarmizi Adam

He received a B. Eng degree in electronics, computer and information engineering in 2011, an MSC degree in 2013 and PhD in electrical engineering in 2019 from International Islamic University Malaysia, Universiti Teknologi Malaysia and Universiti Malaya respectively. His research interests include image processing, signal processing and mathematical optimization.

Dr. Wan Amirul Bin Wan Mohd Mahiyidin

He received the M.Eng. degree from the Imperial College London in 2009, the M.Sc. degree from University of Malaya in 2012, and the Ph.D. degree from University of Canterbury in 2016. He is currently a senior lecturer at the Department of Electrical Engineering, University of Malaya. His research interests are multiple antennas system, cooperative MIMO, channel modelling and positioning system.

Dr. Jafferi Jamaludin

He received a B. Eng degree from Universiti Tenaga Nasional Putrajaya, an M. Eng. Sc. and PhD from Universiti Malaya, Kuala Lumpur, Malaysia. He received Hitachi Global Foundation for postdoctoral research at Keio University, Japan. His research interests include image processing, signal processing, control system and energy management.