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Design, Implementation and Comparative Study of Supervised Classification Algorithms for Object Sorting

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Abstract:*The present study contributes the detailed design, Implementation and comparative studies of supervised classification algorithms such as Nearest Neighbor (NN),k-Nearest Neighbor (k-NN) and Minimum Mean Distance (MMD) along with the distance metrics Maximum, Sum (Manhattan) and Euclidean distances. Classification involves training and testing phases. Training phase teaches the classifier about the types of sample images to classify during the testing phase and saves the class names in a classifier file. Testing phase classifies an unknown sample image into one of the class from classifier file. Total numbers of sample images were divided into the ratio of 30:70 for training and testing respectively. Then classification procedure was performed on sample images for each algorithm with each distance metric. The training and testing VIs for particle and color classification were designed and implemented by using LabVIEW. All the algorithms and distance metrics were analyzed, compared for best results and the maximum accuracy algorithm along with its distance metric is going to implement in real time object sorting application.*
Keywords: *Object Sorting, Supervised Classification Algorithms, Training Phase, Testing Phase, LabVIEW*

I. Introduction

Grouping and tagging of objects with similar properties together, using image processing techniques and statistical classification algorithms for object sorting is the most attention-grabbing research area in the field of automation and instrumentation. Sorting systems remain essential in numerous areas with diverse applications such as in manufacturing industry, libraries, factories, warehouses, pharmacies, supermarkets etc. Yang Tao discusses the advantage of image processing in sorting applications by implementing a sorting system based on the hue extraction of an image processor from the image sensor and image processor performs a color transformation and obtains a single composite hue value for each object for piece of fruit to be sorted [1]. Thomas C. Pearson describes the object sorting system based on video image of an object [2]. MohamadBdiwi discusses about the control system and vision algorithms for library automation and book sorting using integrated vision/force robot control [3]. Roland Szabo implemented an object sorting system based on color using robot arm where webcam is used to identify the color of the object and robot arm is used to place the object in appropriate place [4]. A vision based robot system was developed for 3D pose estimation and picking of the objects in which a video camera surrounded by eight flashes is used to capture the images and CAD tool is used to find the edges of the object using a fully projective formulation [ACB98] of Lowe‘s model based pose estimation algorithm [5]. RaihanFerdousSajal and associates designed an efficient machine vision algorithm for real time image analysis and recognition of different features of Bangladeshi bank notes by using an automatic banknotes sorting system [6].

Image Classification is defined as the process of extracting information/data from an image. The main role of image classification is to detect, recognize and classify the features of an object in an image depending on the type of class [7]. The NN classification algorithm detects the unknown object of a class in an image on the basis of nearest neighbor to the unknown classes from the trained classes. NN is the most widely used classification algorithm in ranking models [13], text categorization [10-12], pattern recognition [8, 9], event recognition [14] and object recognition [15] applications. kNN uses NN rule in which nearest neighbor is calculated from the value of k to specify the number of nearest neighbors to be considered to define a class of sample data point. kNN provides objective, fast, transparent and produces good results over larger areas. The main advantage of kNN algorithm is its simplicity and lack of parametric assumptions [16]. Past researches on Minimum distance classification shows that it is extremely suggested in all image classification applications because of its minimum computation time as it mainly depends on the training data [17].

The present study was focused on the design and implementation of the training and testing VIs for particle and color classification along with distance metrics using LabVIEW. The comparative study was discussed in the results and discussions section. Best results and maximum accuracy algorithm with the corresponding distance metric for both particle and color sorting was used in the real time object sortingapplication.

II. Hardware Features

This section describes the basic hardware units required to implement the supervised classification algorithms. The hardware units used to implement the present work are an image sensor, Illumination unit and PC.

Image Sensor and Illumination Unit

An image sensor, its features and illumination unit used in the present work are described in this section. Image sensor is the first system component to acquire the image of object and to convert it into electrical signal. Most common type of image sensors used is Charge Coupled Device (CCD) and Complementary Metal Oxide Semiconductor (CMOS) image sensors. In the present work CMOS image sensor was used because of producing digital bits output and its compatibility for interfacing with electronic devices, microcontrollers, PC etc. Since the image sensor produce digital output it was interfaced with the Universal Serial Bus (USB) controller to communicate with PC. The specifications of CMOS image sensor used in the present work are provided in the Table 1.

Description	**Value**
Resolution	8 Mega Pixel
Interface	USB2.0
Capture Size	640X480
Image Focus	3cm to infinity
Signal Noise Ratio	48DB

Table 1: Specifications of CMOS Image Sensor

CMOS image sensor was built with an array of photo detectors that contain amplifiers, noise-correction and digitization circuit. Generally an image sensor was fixed with lens and interfaced with the microcontroller and a flash memory to get the data of images to PC. Lens was fixed to get the high quality images from the image sensor. The image sensor produces serial digital data output. It was interfaced with EEPROM and USB microcontroller. EEPROM used in the present work is Pm25LV512, a serial EEPROM manufactured by Programmable Microelectronics Corporation. It comes with 512 Kbits of memory that consumes low power with 3.3V and cost effective memory. USB controller used in the present work is VC0326 which was embedded with 8-bit microcontroller, 10-bit image processor, JPEG encoder engine, inbuilt ADC, audio and video class USB support and complies with USB 2.0 protocols for transferring data to PC.

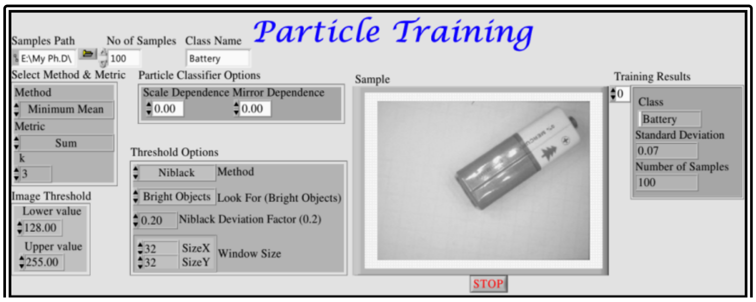


Fig. 1 Front Panel of Particle Training

Image sensor was equipped with illumination unit to capture clear and optimal images with ease. Illumination unit consists of 12V LEDs which are connected in series and fixed in such a way that the lighting was focused on the object. 35 LEDs are connected with 7 arrays and each array contains three LEDs and 3 current limiting resistors.

III. Supervised Classification Algorithms using LabVIEW

This section describes the application design of particle training, particle testing, color training and color testing in LabVIEW.

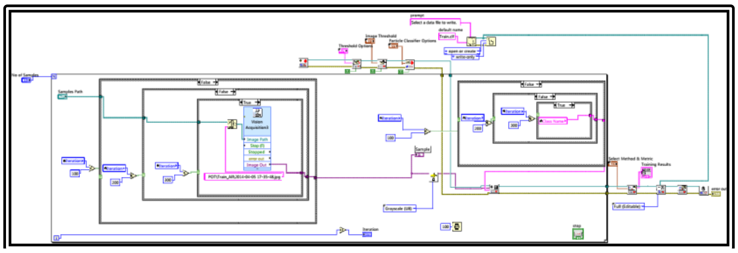


Fig. 2 Block Diagram of Particle Training

1.1 Particle Training

Particle training VI teaches the classifier session with number of images to generate a classifier file with the class labels. The training procedure was explained in the principle. Fig. 1 shows the front panel of the particle training phase. It consists of Sample Path, No of Samples, Class Name, Select Method & Metric, Particle Classifier Options, Image Thresholding, Threshold Options, Sample and Training Results.Sample Path is a file path control which is used to enter the file path of the sample images and it returns the location of the directory. No of Samples is a 32-bit integer control used to enter the number of samples. Class Name is a string used to enter the class name of the set of sample images. Select Method & Metric isa type definition of IMAQ classifier Nearest Neighbor options and cluster of three 32-bit integer control elements Method, Metric and k. Method is used to specify the algorithm of the classifier session, options include NN, kNN and MMD algorithms. Metric is used to specify the distance metric of the classifier session; options include Maximum, Sum (Manhattan)and Euclidean metrics. kis used to enter an odd value when Method is kNN.

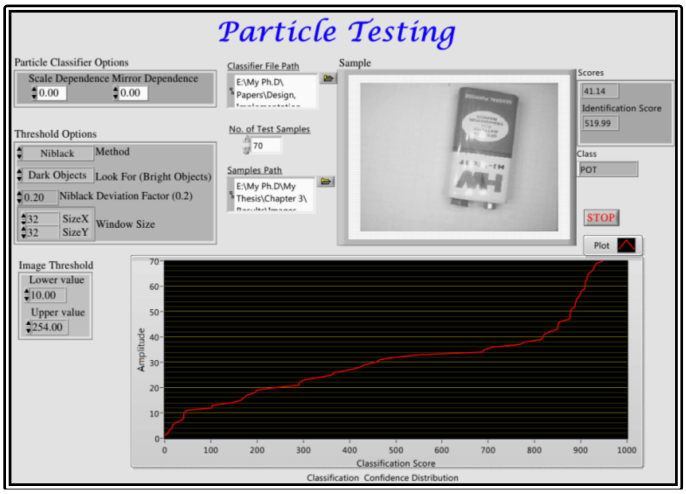


Fig. 3 Front Panel of Particle Testing

Particle Classifier Options is a type definition of IMAQ Classification Particle Classification Options and a cluster of two 32-bit real control elements Scale Dependency and Mirror Dependency. Scale Dependency is used to determine the relative importance from 0 to 1000 of scale when classifying particles. If it is 0 then classifying is performed independent of scale value. Mirror Dependency determines the relative importance from 0 to 1000 of mirror symmetry when classifying particles. Image Threshold is the type definition of IMAQ Threshold Range and cluster of two 32-bit real control elements Lower Value and Upper Value. Lower Value and Upper Value are the lowest and highest pixel values used during a threshold. Threshold Options is the type definition of IMAQ Classification particle Local Threshold Options anda cluster of 4 elements of which Method indicates the local thresholding algorithm and Look For indicates the type of objects looking for, are 32-bit integer control elements, Niblack Deviation Factor is 64-bit real control element that specifies the constantused in the Niblack algorithmand Window Size is a cluster of 2 elements SizeX and SizeY which specifies the size of the window the VI uses when calculating a local threshold. SizeX and SizeY are the sizes of windows in x and y dimensions respectively. Sample is the type definition of IMAQ Image which is used to display the input sample images.

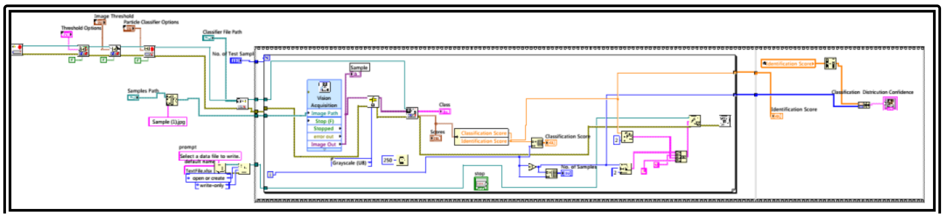


Fig. 4 Block Diagram of Particle Testing

Training Results is an array of statistical information for each class in the classifier session and a cluster of 3 elements Class, Standard Deviation and Number of Samples.Class is the string of class name which the VI reads. Standard Deviation is the standard deviation from the mean of all samples in class. Number of Samples is the no. of samples in the class.

Fig. 5 Front Panel of Color Training

Fig. 2 shows the block diagram of particle training. The main building blocks of Particle training block diagram are IMAQ Create Particle Classifier VI, IMAQ Particle Classifier Manual Threshold Options VI, IMAQ Particle Classifier Options VI, IMAQ Add Classifier Sample VI, IMAQ Train Nearest Neighbor VI,IMAQ Write Classifier File VI and IMAQ Dispose Classifier VI. IMAQ Create Particle Classifier Creates a particle classifier session. IMAQ Particle Classifier Options Configures the particle classifier options for the classifier session. IMAQ Particle Classifier Manual Threshold Options configures the manual threshold options for the given session and sets the session to use manual threshold.

IMAQ Add Classifier Sample Assigns a new image sample to the specified class in Classifier Session. The new sample is based on an ROI in the image. The sample is assigned to a specific class. IMAQ Train Nearest Neighbor VI sets the classifier session to use the Nearest Neighbor Classifier engine, and configures the Nearest Neighbor parameters it will use. IMAQ Write Classifier File VI writes a classifier session to the file specified in File Path. This VI saves the exact state of the classifier session. IMAQ Dispose Classifier VI destroys a classifier session and frees the space it occupied in memory. You must call IMAQ Dispose Classifier when the application no longer needs the session. This VI is required for each classifier session create.

1.2 Particle Testing

Fig. 3 shows the front panel of the particle testing. Particle test front panel uses few similar elements in the front panel of particle training. Hence the details of those elements are not presented in this section. Excluding the elements of Fig. 1 particle testing uses a Classifier File Path, No of Test Samples, Scores, Class and Classification Distribution Confidence. Classifier File Path is the complete file path name of the classifier file to read. No of Test Samples is a 32-bit integer control element to provide number of samples to read. Scores is the cluster of two 32-bit real element indicators that returns estimations of how well the classifier session classified the input. The score can vary from 0 to 1000, where 1000 represents the best possible score. Class is theclass name into which the classifier session categorizes the input sample. Classification Distribution Confidence is the histogram of classification score and amplitude, where amplitude represents the number of samples.

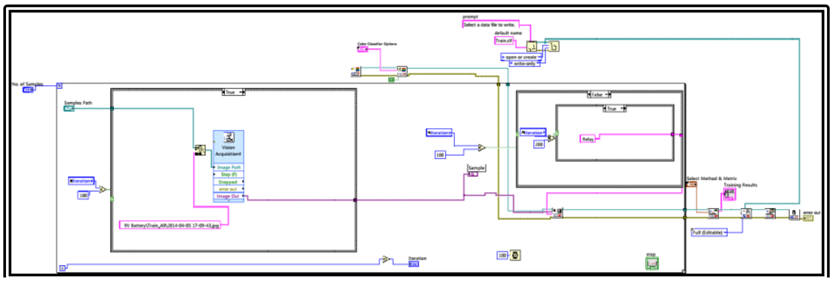


Fig. 6 Block Diagram of Color Training

Fig. 4 shows the block diagram of the particle testing. Particle testing block diagram uses few similar elements as in Fig. 2 such as IMAQ Create Particle Classifier VI, IMAQ Particle Classifier Manual Threshold Options VI and IMAQ Particle Classifier Options VI. The only difference is the Get/Set Boolean control. For particle training and testing Get/Set is 1 and 0 respectively. Excluding the elements in Fig. 2 particle testing consists of IMAQ Read Classifier File VI and IMAQ Classify VI. IMAQ Read Classifier File VI Reads a classifier session from the file specified by File Path. IMAQ Classify VI Classifies the image sample and gives classification score.

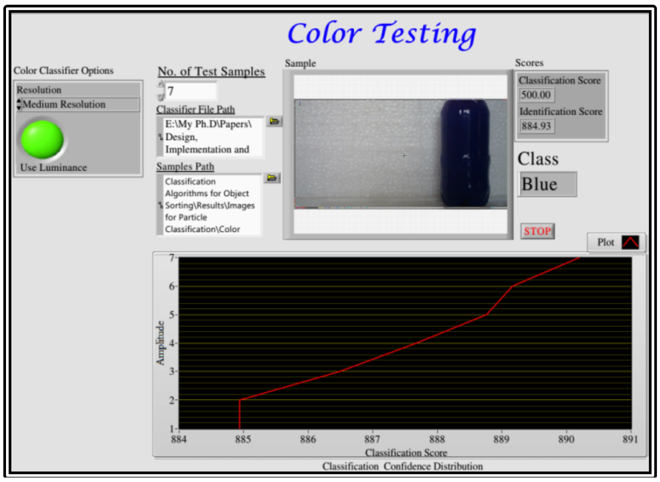


Fig. 7 Front Panel of Color Test

1.3 Color Training

Fig. 5 shows the front panel of color training. Color training front panel uses few similar elements as in Fig. 3 such as Sample Path, No of Samples, Class Name, Select Method & Metric, Sample and Training Results. Excluding the elements in Fig. 3 color training consists of only one element Color Classifier Options. It provides options to set the color resolution like high, medium and low of a feature and to enable/disable luminance band. Color Classifier Options is the type definition of IMAQ Classification Color Options and a cluster of one Resolution which is the type definition of IMAQ Classification Color Resolution and one Boolean control Use Luminance.

Fig. 6 shows the block diagram of the color training. Color training block diagram uses few similar elements as in Fig. 2 such as IMAQ Add Classifier Sample VI, IMAQ Train Nearest Neighbor VI,IMAQ Write Classifier File VI and IMAQ Dispose Classifier VI. Excluding the elements in Fig. 2 color training block diagram consists of IMAQ Create Color Classifier VI and IMAQ Color Classifier Options. IMAQ Create Color Classifier VI creates a color classifier session. IMAQ Color Classifier Options configures the color classifier options for the classifier session.

1.4 Color Testing

Fig. 7 shows the front panel of color testing. Color testing front panel uses all the elements as in Fig. 1 such as Classifier File path, No of Test Samples, Samples Path, Sample, Scores, Class Classification Distribution Confidence and Color Classification options from Fig. 3.

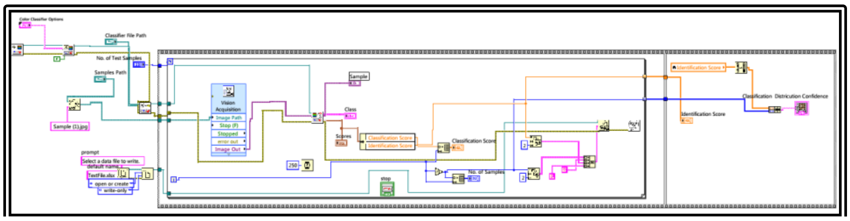


Fig. 8 Block Diagram of Color Test

Fig. 8 shows the block diagram of color testing. Color testing uses elements from particle testing and color training block diagram as shown in Fig. 2 and Fig. 4 excluding IMAQ Classify Color Advanced VI. IMAQ Classify Color Advanced VI classifies the image sample located in the given ROI and returns advanced information, such as the Sample Results.

IV. Methodology

In [18], methodology was explained and Classification Accuracy (%), Misclassification Rate and kappa coefficientwere evaluated only for one set of samples. Inthe present work an additional parameter classification predictive value was explored. It indicates the probability that a sample classified into a given class belongs to that class. Columns of the table were used to determine the predictive value, per class, of a classifier. Each column represents a class into which the classifier classifies samples. The values in the columns indicate how many samples of each class have been classified into the class represented by the column.

$$\mathrm{ClassificationPredictiveValue(PV)} = \frac{\mathrm{No.ofsamplesclassifiedcorrectly}}{\mathrm{TotalNo.ofsamplesclassifiedintotheclass}}$$

LabVIEW programs were developed for training and testing of particle and color objects. The same parameters were evaluated to select the best algorithm. Particle objects considered are nuts, bolts and electronic components. Color liquid filled in bottles is considered as colored objects.

Fig. 11 shows the flow chart of particle and color classification procedure. Flow charts show that initially it starts a new classifier session using IMAQ Create Particle Classifier VI and acquires necessary inputs from the user through front panel of the LabVIEW using Sample Path, No of Samples, Class Name, Select Method & Metric, Particle Classifier Options, Image Thresholding, Threshold Options, Classifier File Path andColor Classifier Options. Input images of particle training and testing are converted from 32-bit RGB to 8-bit Gray scale images as shown in Fig. 9 (a) & (c) whereas color training and testing uses 32-bit RGB images directly as shown in Fig. 9 (b) & (d). Draw an ROI (Region of Interest) if the input image contains more than one object. Since an input image contains only one object no need to draw an ROI. Training procedure adds the sample to the classifier session for both particle and color using IMAQ Add Classifier Sample VI. Next the sequence checks whether the iteration of for loop for No. of samples reached or not. If yes train the classifier using IMAQ Train Nearest Neighbor VI and write the training results using such as number of samples per class, class name and trained classifier options using IMAQ Write Classifier File VI. Finally close the classifier session for training using IMAQ Dispose Classifier.

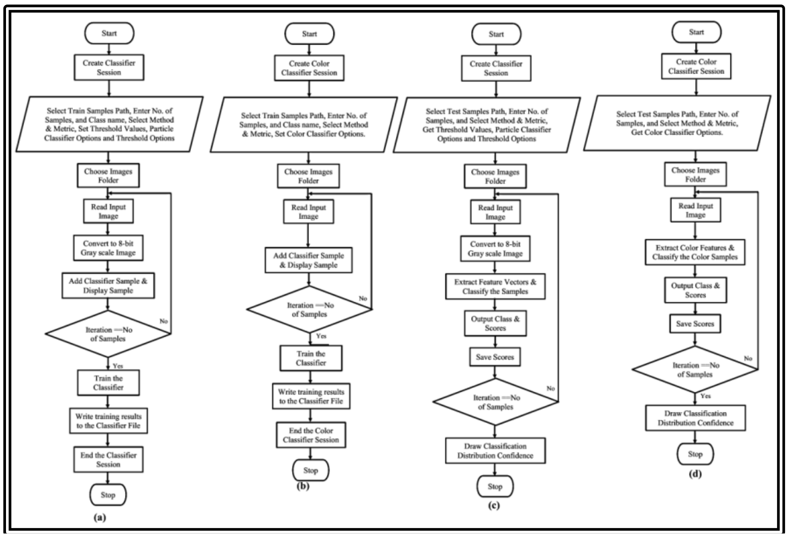


Fig. 9 Flow Chart of Particle and Color Classification (a) Particle Training (b) Particle Testing (c) Color Training and (d) Color Testing

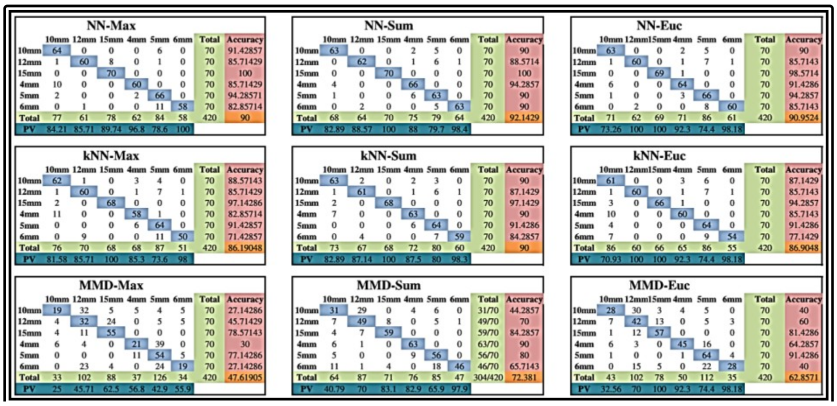
In the testing procedure particle testing remains same as particle training until 32-bit to 8-bit image conversion as shown in Fig. 9 (c). Then IMAQ Classify extracts the feature vectors of the test sample. There are total 8 invariant features such as circularity of the sample, degree of elongation of the sample, convexity of the sample shape, detailed description of the convexity of a sample shape, discrimination of samples with holes, detailed discrimination of samples with holes, spread of the sample and slenderness of the sample. Depending upon the nature, dimensions etc. of the sample, feature vectors are extracted. IMAQ Classify classifies the samples and provides the outputs such as class name, classification score and identification scores.

IMAQ Classify Color Advanced VI extracts color features to classify the color sample images. It converts the color sample image to HSL color space for calculating hue, saturation and luminance histograms. The hue and saturation histograms each contain 256 values. Decrease the luminance histogram to 8 values that are suppressed by 12.5%. By doing this, IMAQ Classify Color Advanced VI accentuates the color information. To get a high resolution color feature combine the 520 hue, saturation and luminance values. By applying a dynamic mask to the high resolution color feature one can get medium and low resolution color features. These are the subsets of high resolution color features. The medium resolution color feature contains 128 hue and saturation values and 8 luminance values for a total of 136 values. The low resolution color feature contains 64 hue and saturation values and 8 luminance values for a total of 72 values.

A histogram is drawn which is known as classification confidence distribution. The output of the classification confidence distribution is a good indicator of the classifier performance.

V. Results and Discussions

This section gives results and discusses the importance of classification algorithm and distance metrics for real time object sorting application of particle and color. Total 3 sets of images were considered for particle classification. It uses 4mm, 5mm, 6mm, 10mm, 12mm and 15mm diameter nuts, 1inch length 4mm, 5mm, 6mm, 10mm and 12mm diameter bolts and electronic spares such as 9V DC battery, potentiometer, 6V DC ice cube relay and toggle switches to evaluate the classifiers performance. Color classification uses the real colors filled in the bottle. Total 9 colors are used to evaluate the classifiers performance.



NN-Max

	10mm	12mm	15mm	4mm	5mm	6mm	Total	Accuracy
10mm	64	0	0	0	6	0	70	91.42857
12mm	1	60	8	0	1	0	70	85.71429
15mm	0	0	70	0	0	0	70	100
4mm	10	0	0	60	0	0	70	85.71429
5mm	2	0	0	2	66	0	70	94.28571
6mm	0	1	0	0	11	58	70	82.85714
Total	77	61	78	62	84	58	420	90
PV	84.21	85.71	89.74	96.8	78.6	100		

NN-Sum

	10mm	12mm	15mm	4mm	5mm	6mm	Total	Accuracy
10mm	63	0	0	2	5	0	70	90
12mm	0	62	0	1	6	1	70	88.5714
15mm	0	0	70	0	0	0	70	100
4mm	4	0	0	66	0	0	70	94.2857
5mm	1	0	0	6	63	0	70	90
6mm	0	2	0	0	5	63	70	90
Total	68	64	70	75	79	64	420	92.1429
PV	82.89	88.57	100	88	79.7	98.4		

NN-Euc

	10mm	12mm	15mm	4mm	5mm	6mm	Total	Accuracy
10mm	63	0	0	2	5	0	70	90
12mm	1	60	0	1	7	1	70	85.7143
15mm	0	0	69	1	0	0	70	98.5714
4mm	6	0	0	64	0	0	70	91.4286
5mm	1	0	0	3	66	0	70	94.2857
6mm	0	2	0	0	8	60	70	85.7143
Total	71	62	69	71	86	61	420	90.9524
PV	73.26	100	100	92.3	74.4	98.18		

kNN-Max

	10mm	12mm	15mm	4mm	5mm	6mm	Total	Accuracy
10mm	62	1	0	3	4	0	70	88.57143
12mm	1	60	0	1	7	1	70	85.71429
15mm	2	0	68	0	0	0	70	97.14286
4mm	11	0	0	58	1	0	70	82.85714
5mm	0	0	0	6	64	0	70	91.42857
6mm	0	9	0	0	11	50	70	71.42857
Total	76	70	68	68	87	51	420	86.19048
PV	81.58	85.71	100	85.3	73.6	98		

kNN-Sum

	10mm	12mm	15mm	4mm	5mm	6mm	Total	Accuracy
10mm	63	2	0	2	3	0	70	90
12mm	1	61	0	1	6	1	70	87.1429
15mm	2	0	68	0	0	0	70	97.1429
4mm	7	0	0	63	0	0	70	90
5mm	0	0	0	6	64	0	70	91.4286
6mm	0	4	0	0	7	59	70	84.2857
Total	73	67	68	72	80	60	420	90
PV	82.89	87.14	100	87.5	80	98.3		

kNN-Euc

	10mm	12mm	15mm	4mm	5mm	6mm	Total	Accuracy
10mm	61	0	0	3	6	0	70	87.1429
12mm	1	60	0	1	7	1	70	85.7143
15mm	3	0	66	1	0	0	70	94.2857
4mm	10	0	0	60	0	0	70	85.7143
5mm	4	0	0	0	64	0	70	91.4286
6mm	7	0	0	0	9	54	70	77.1429
Total	86	60	66	65	86	55	420	86.9048
PV	70.93	100	100	92.3	74.4	98.18		

MMD-Max

	10mm	12mm	15mm	4mm	5mm	6mm	Total	Accuracy
10mm	19	32	5	5	4	5	70	27.14286
12mm	4	32	24	0	5	5	70	45.71429
15mm	4	11	55	0	0	0	70	78.57143
4mm	6	4	0	21	39	0	70	30
5mm	0	0	0	11	54	5	70	77.14286
6mm	0	23	4	0	24	19	70	27.14286
Total	33	102	88	37	126	34	420	47.61905
PV	25	45.71	62.5	56.8	42.9	55.9		

MMD-Sum

	10mm	12mm	15mm	4mm	5mm	6mm	Total	Accuracy
10mm	31	29	0	4	6	0	31/70	44.2857
12mm	7	49	8	0	5	1	49/70	70
15mm	4	7	59	0	0	0	59/70	84.2857
4mm	6	1	0	63	0	0	63/70	90
5mm	5	0	0	9	56	0	56/70	80
6mm	11	1	4	0	18	46	46/70	65.7143
Total	64	87	71	76	85	47	304/420	72.381
PV	40.79	70	83.1	82.9	65.9	97.9		

MMD-Euc

	10mm	12mm	15mm	4mm	5mm	6mm	Total	Accuracy
10mm	28	30	3	4	5	0	70	40
12mm	7	42	13	0	5	3	70	60
15mm	1	12	57	0	0	0	70	81.4286
4mm	6	3	0	45	16	0	70	64.2857
5mm	1	0	0	1	64	4	70	91.4286
6mm	0	15	5	0	22	28	70	40
Total	43	102	78	50	112	35	420	62.8571
PV	32.56	70	100	92.3	74.4	98.18		

Fig. 10 Classification Distribution Tables for Nuts

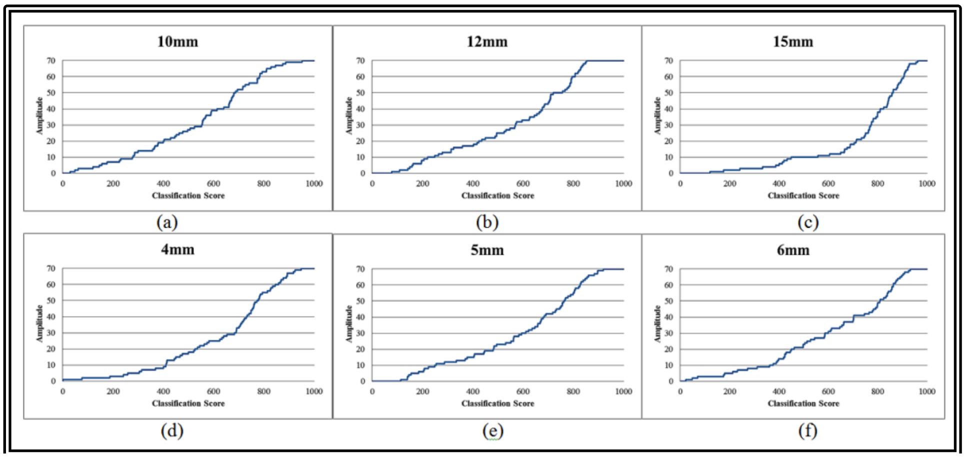


Fig. 11 Classification Confidence Distribution of NN-Sum for Nuts

Fig. 12 shows the classification distribution tables of nuts for all algorithms and distance metrics.

Results have been taken for total nine combinations in which NN-Sum (Nearest Neighbor with Sum distance metric) shows the highest accuracy of 92.1429% among all. Hence the classification confidence distribution was taken for NN-Sum. Fig. 13 (a), (b), (c), (d), (e) and (f) shows the classification confidence (Classification Score) distribution for 10mm, 12mm, 15mm, 4mm, 5mm and 6mm nuts. From the figure it is clear that the classification score threshold varies for each nut type. By keeping the threshold scores 121.33, 163.18, 121, 77.45, 139.66 and 49.46 one can eliminate 3, 4, 0, 1, 1, and 1 other sized nuts whereas 1, 2, 0, 1, 1, and 1 same sized nuts can be ignored for 10mm, 12mm, 15mm, 4mm, 5mm and 6mm nuts. For all algorithms and distance metrics classification accuracy and classification predictive values are given in Fig. 12 with the label Accuracy (in orange color) and PV(in blue color)for each class respectively.

Fig. 12 shows the classification distribution tables of bolts for all algorithms and distance metrics. Results have been taken for total nine combinations in which NN-Sum shows the highest accuracy of 90.5714% among all. Hence the classification confidence distribution was taken for NN-Sum. Fig. 13 (a), (b), (c), (d), and (e) shows the classification confidence distribution for 1inch 10mm, 12mm, 4mm, 5mm and 6mm nuts. From the figure it is clear that the classification score threshold varies for each bolt type. By keeping the threshold scores 30.17, 207.59, 44.15, 207.18, and 44.06 one can eliminate 4, 5, 0, 7, and 0 other sized nuts whereas 2, 3, 0, 2, and 0 same sized nuts can be ignored for 1inch 10mm, 12mm, 4mm, 5mm and 6mm bolts.

NN-Max

	10mm	12mm	4mm	5mm	6mm	Total	Accuracy
10mm	64	0	0	0	6	70	91.42857
12mm	1	60	8	0	1	70	85.71429
4mm	0	0	69	1	0	70	98.57143
5mm	9	3	0	55	3	70	78.57143
6mm	8	0	0	5	57	70	81.42857
Total	82	63	77	61	67	350	87.14286
PV	84.21	85.71	89.61	90.16	85.07		

NN-Sum

	10mm	12mm	4mm	5mm	6mm	Total	Accuracy
10mm	53	11	0	5	1	70	75.71429
12mm	6	64	0	0	0	70	91.42857
4mm	0	0	70	0	0	70	100
5mm	7	2	0	61	0	70	87.14286
6mm	0	0	0	1	69	70	98.57143
Total	66	77	70	67	70	350	90.57143
PV	69.74	91.43	100	91	98.57		

NN-Euc

	10mm	12mm	4mm	5mm	6mm	Total	Accuracy
10mm	50	13	0	5	2	70	71.42857
12mm	10	60	0	0	0	70	85.71429
4mm	0	0	69	1	0	70	98.57143
5mm	7	3	0	60	0	70	85.71429
6mm	3	0	0	3	64	70	91.42857
Total	70	76	69	69	66	350	86.57143
PV	65.79	85.71	100	86.96	96.97		

kNN-Max

	10mm	12mm	4mm	5mm	6mm	Total	Accuracy
10mm	48	14	0	6	2	70	68.57143
12mm	12	58	0	0	0	70	82.85714
4mm	0	0	67	3	0	70	95.71429
5mm	9	4	0	50	7	70	71.42857
6mm	9	0	0	4	57	70	81.42857
Total	78	76	67	63	66	350	80
PV	63.16	82.86	100	79.37	86.36		

kNN-Sum

	10mm	12mm	4mm	5mm	6mm	Total	Accuracy
10mm	42	22	0	4	2	70	60
12mm	12	58	0	0	0	70	82.85714
4mm	0	0	70	0	0	70	100
5mm	6	4	0	58	2	70	82.85714
6mm	0	0	0	1	69	70	98.57143
Total	60	84	70	63	73	350	84.85714
PV	55.26	82.86	100	92.1	94.52		

kNN-Euc

	10mm	12mm	4mm	5mm	6mm	Total	Accuracy
10mm	45	19	0	4	2	70	64.28571
12mm	12	58	0	0	0	70	82.85714
4mm	0	0	69	1	0	70	98.57143
5mm	7	3	0	56	4	70	80
6mm	4	0	0	1	65	70	92.85714
Total	68	80	69	62	71	350	83.71429
PV	59.21	82.86	100	90.32	91.55		

MMD-Max

	10mm	12mm	4mm	5mm	6mm	Total	Accuracy
10mm	12	45	0	6	7	70	17.14286
12mm	8	48	2	10	2	70	68.57143
4mm	1	1	58	10	0	70	82.85714
5mm	11	6	24	21	8	70	30
6mm	16	6	10	15	23	70	32.85714
Total	48	106	94	62	40	350	46.28571
PV	15.79	68.57	61.7	33.87	57.5		

MMD-Sum

	10mm	12mm	4mm	5mm	6mm	Total	Accuracy
10mm	36	27	0	5	2	70	51.42857
12mm	2	55	0	13	0	70	78.57143
4mm	0	0	70	0	0	70	100
5mm	9	9	0	50	2	70	71.42857
6mm	10	0	0	0	60	70	85.71429
Total	57	91	70	68	64	350	77.42857
PV	47.37	78.57	100	73.5	93.75		

MMD-Euc

	10mm	12mm	4mm	5mm	6mm	Total	Accuracy
10mm	16	44	0	9	1	70	22.85714
12mm	8	48	0	14	0	70	68.57143
4mm	1	0	68	1	0	70	97.14286
5mm	13	6	9	39	3	70	55.71429
6mm	15	3	0	16	36	70	51.42857
Total	53	101	77	79	40	350	59.14286
PV	21.05	68.57	88.31	49.37	90		

Fig. 12 Classification Distribution Tables for 1inch Bolts

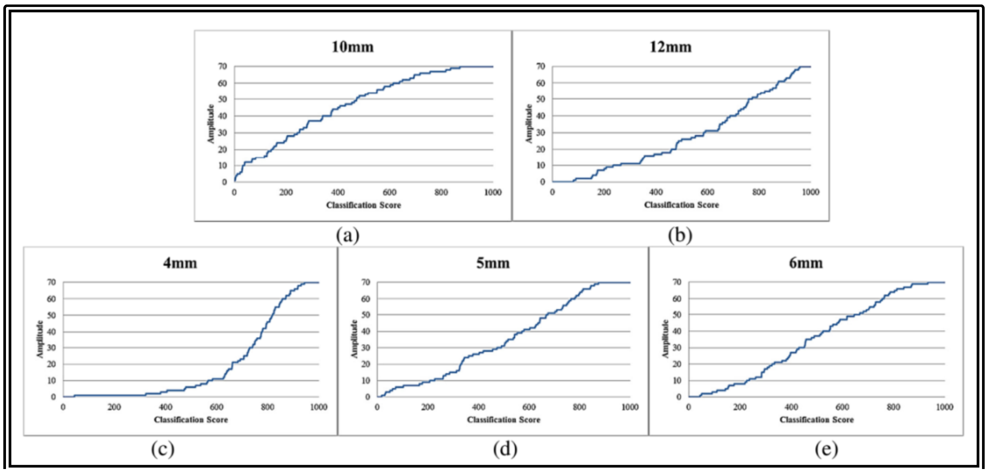
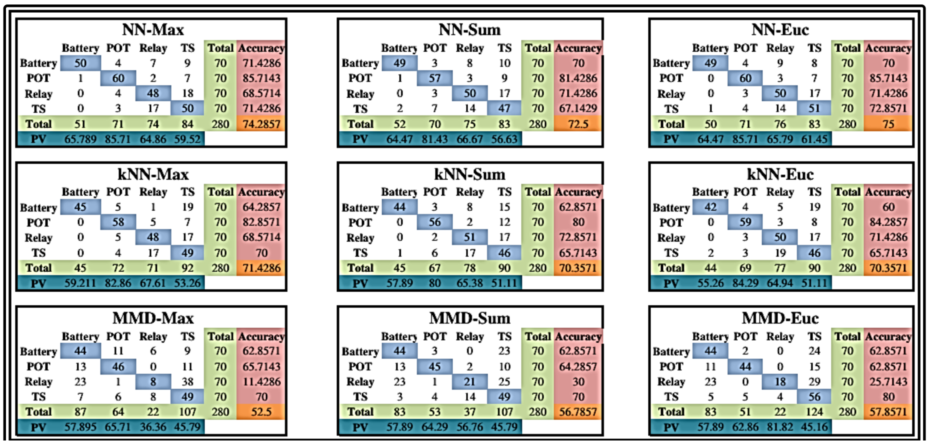


Fig. 13 Classification Confidence Distribution of NN-Sum for Bolts

Fig. 14 shows the classification distribution tables of electronic spares for all algorithms and distance metrics. Results have been taken for total nine combinations in which NN-Euc (Nearest Neighbor with Euclidean distance metric) shows the highest accuracy of 75% among all. Hence the classification confidence distribution was taken for NN-Euc. Fig. 15 (a), (b), (c), and (d) shows the classification confidence distribution for Battery, POT, Relay and Toggle Switch (TS). From the figure it is clear that the classification score threshold varies for each spare. By keeping the threshold scores 686.89, 0, 210.14 and 128.38 one can eliminate 21, 0, 7, and 9 other spares whereas 12, 0, 6, and 3 same spare for 1inch Battery, POT, Relay and TS.



NN-Max

	Battery	POT	Relay	TS	Total	Accuracy
Battery	50	4	7	9	70	71.4286
POT	1	60	2	7	70	85.7143
Relay	0	4	48	18	70	68.5714
TS	0	3	17	50	70	71.4286
Total	51	71	74	84	280	74.2857
PV	65.789	85.71	64.86	59.52		

NN-Sum

	Battery	POT	Relay	TS	Total	Accuracy
Battery	49	3	8	10	70	70
POT	1	57	3	9	70	81.4286
Relay	0	3	50	17	70	71.4286
TS	2	7	14	47	70	67.1429
Total	52	70	75	83	280	72.5
PV	64.47	81.43	66.67	56.63		

NN-Euc

	Battery	POT	Relay	TS	Total	Accuracy
Battery	49	4	9	8	70	70
POT	0	60	3	7	70	85.7143
Relay	0	3	50	17	70	71.4286
TS	1	4	14	51	70	72.8571
Total	50	71	76	83	280	75
PV	64.47	85.71	65.79	61.45		

kNN-Max

	Battery	POT	Relay	TS	Total	Accuracy
Battery	45	5	1	19	70	64.2857
POT	0	58	5	7	70	82.8571
Relay	0	5	48	17	70	68.5714
TS	0	4	17	49	70	70
Total	45	72	71	92	280	71.4286
PV	59.211	82.86	67.61	53.26		

kNN-Sum

	Battery	POT	Relay	TS	Total	Accuracy
Battery	44	3	8	15	70	62.8571
POT	0	56	2	12	70	80
Relay	0	2	51	17	70	72.8571
TS	1	6	17	46	70	65.7143
Total	45	67	78	90	280	70.3571
PV	57.89	80	65.38	51.11		

kNN-Euc

	Battery	POT	Relay	TS	Total	Accuracy
Battery	42	4	5	19	70	60
POT	0	59	3	8	70	84.2857
Relay	0	3	50	17	70	71.4286
TS	2	3	19	46	70	65.7143
Total	44	69	77	90	280	70.3571
PV	55.26	84.29	64.94	51.11		

MMD-Max

	Battery	POT	Relay	TS	Total	Accuracy
Battery	44	11	6	9	70	62.8571
POT	13	46	0	11	70	65.7143
Relay	23	1	8	38	70	11.4286
TS	7	6	8	49	70	70
Total	87	64	22	107	280	52.5
PV	57.895	65.71	36.36	45.79		

MMD-Sum

	Battery	POT	Relay	TS	Total	Accuracy
Battery	44	3	0	23	70	62.8571
POT	13	45	2	10	70	64.2857
Relay	23	1	21	25	70	30
TS	3	4	14	49	70	70
Total	83	53	37	107	280	56.7857
PV	57.89	64.29	56.76	45.79		

MMD-Euc

	Battery	POT	Relay	TS	Total	Accuracy
Battery	44	2	0	24	70	62.8571
POT	11	44	0	15	70	62.8571
Relay	23	0	18	29	70	25.7143
TS	5	5	4	56	70	80
Total	83	51	22	124	280	57.8571
PV	57.89	62.86	81.82	45.16		

Fig. **14 Classification Distribution Tables for Electronic Parts**

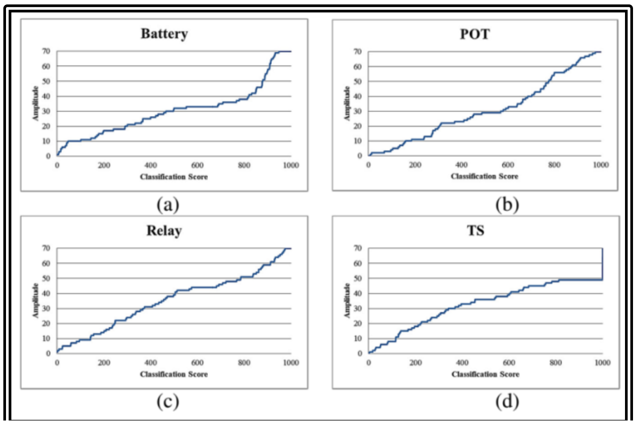


Fig. 15 Classification Confidence Distribution of NN-Sum for Bolts

Fig. 16 shows the classification distribution tables of color for all algorithms and distance metrics. Results have been taken for total 9 colors with nine combinations in which NN-Sum and MMD-Sum shows the highest accuracy of 95.238% among all. Since 7 sample images were considered for testing, classification confidence distribution was not drawn.

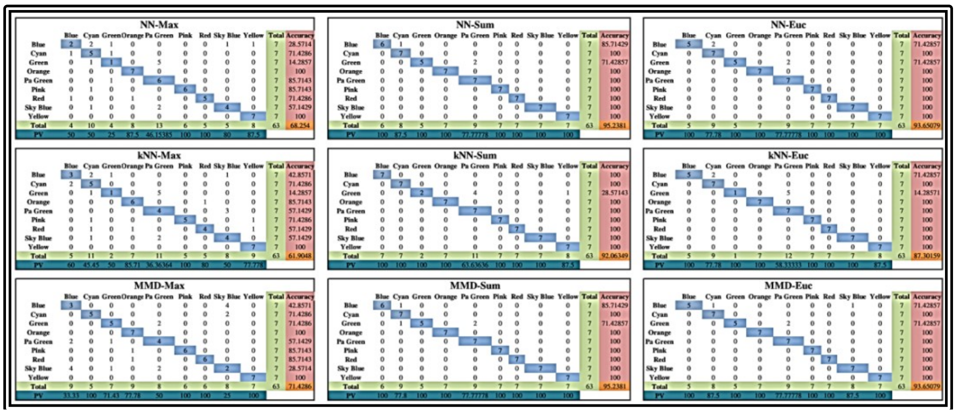


Fig. 16 Classification Distribution Tables for Color Bottles

	Nuts NN-Sum	**Bolts** NN-Sum	**Elec-Spares** NN-Euc	**Color** NN/MMD-Sum
Accuracy (%)	92.1429	90.5714	75	95.2381
Misclassification Rate	0.07857	0.09429	0.25	0.04762
Kappa Coefficient	0.906	0.882	0.667	0.946

Table 2: Classification Parameters for Selected Algorithms

Misclassification rate and kappa coefficient was calculated for nuts, bolts, electronic spares, colors on each algorithm and distance metrics. Table 2 shows the best values of classification parameters such as accuracy, misclassification rate and kappa coefficient among all. From the investigations it is clear that NN-Sum can be used for nuts and bolts and NN-Euc can be used for electronic spares in real time object sorting application. Both NN-Sum and MMD-Sum can be used in real time color bottles sorting application.

VI. Conclusion

From the investigations it is clear that NN-Sum can be used for nuts and bolts and NN-Euc can be used for electronic spares in real time object sorting application. Both NN-Sum and MMD-Sum can be used in real time color bottles sorting application.However, the accuracy of the algorithms depends on the robustness and quality constraints of training dataset. Different environmental conditions and selection of dataset also affects the classification accuracy.

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