CFS- InfoGain based Combined Shape-based Feature Vector for Signer Independent ISL Database

Garima Joshi[1], Renu Vig[1] and Sukhwinder Singh[2]
[1]*Electronics and Communication Engineering Department, UIET, Panjab University, Chandigarh, India*
[2]*Computer Science and Engineering Department, UIET, Panjab University, Chandigarh, India*
joshi_garima5@yahoo.com, renuvig@hotmail.com, sukhdalip@pu.ac.in

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Abstract: In Sign language Recognition (SLR) system, signs are identified on the basis of hand shapes. Zernike Moments (ZM) are used as an effective shape descriptor in the field of Pattern Recognition. These are derived from orthogonal Zernike polynomial. The Zernike polynomial characteristics change as order and iteration parameter are varied. Observing their behaviour gives an insight into the selection of a particular value of ZM as a part of an optimal feature vector. The performance of ZMs can be improved by combining it with other features, therefore, ZMs are combined with Hu Moments (HM) and Geometric features (GF). An optimal feature vector of size 56 is proposed for ISL dataset. The importance of the internal edge details to address issue of hand-over-hand occlusion is also highlighted in the paper. The proposed feature set gives high accuracy for Support Vector Machine (SVM), Logistic Model Tree (LMT) and Multilayer Perceptron (MLP). However, the accuracy of Bayes Net (BN), Nave Bayes (NB), J48 and k- Nearest Neighbour (k-NN) improves significantly for Info Gain based normalized feature set.

1 INTRODUCTION

Sign Language (SL) is a natural language of the deaf community. The expression varies in terms of regional accents and dialects in SL. Across the globe, countries have their own SL, for example, the American Sign Language (ASL), the British Sign Language (BSL), the Indian Sign Language (ISL), the French Sign Language (FSL), and many more. ISL is highly structured and there is some influence of BSL. ISL and BSL use double hands mostly. SL interpreters are required to facilitate communication between the person using SL and a non-signing individual (Zeshan, Vasishta and Sethna, 2005).

A system that can recognize SL can be used to automatically act as an interpreter for SL. Sign Language Recognition (SLR) system translates the information represented by hand gesture and converts them into text (Rautaray and Agrawal, 2015). In finger spelled SL, English alphabets are represented by hand shape. The name of people, places and abbreviations are finger-spelled in SL. SLR should be capable of classifying the signed alphabets. There is a considerable variation in signs made by different people. SLR system must be capable of recognizing the sign performed by any user. It should be a user independent system. Ni *et. al.* (2015) presented a survey of signer-independent SLR system design. They reported that system performance decreases considerably in the case of a subject independent system as the inter-subject difference can be large. They also highlighted the need to design subject independent datasets because the learning algorithms demand an appropriate number of database samples to train the system.

Various signer independent SLR systems are reported in literature. A brief overview of these systems is presented in Table 1. Important requisites associated with design of SLR system include a standard signer independent database and to find the feature set which is capable of representing the attributes of a sign.

2 PROPOSED FRAMEWORK

The proposed framework is shown in Figure 1. It is designed to evaluate the performance of shape based features for a signer independent SL dataset. Experiments have been performed to realize the following

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Table 1: Literature Survey on Existing Signer Independent Vision based Systems.

Reference	Sign	Signer	Repetition	Features	Classifier	Accuracy
Ong and Ranganath (2004)	20	8	10	Geometric(6)	BN	85
Rousan *et. al.* (2009)	30	18	50	DCT(50)	HMM	94.2
Kelly *et. al.*(2010)	10	24	3	Eigen Space	SVM (SF+HM)	91.8
Shanableh and Assaleh (2011)	23	3	–	DCT(70)	kNN	87
Bhuyan *et. al.* (2011)	8	10	5	Hand Geometry+ HTD(186)	Distance Measure	93.4
Singha and Das (2013)	24	20	–	PCA(50)	Distance Measure	96.25
Auephanwiriyakul *et. al.* (2013)	10	20	–	SIFT(128)	HMM	76.56
Kausar *et. al.* (2016)	37	–	–	Polynomial Parameters	k-NN	92

research objectives:

- To study the behavior of Zernike radial polynomial with variation in its order and iterations.
- To study the performance of ZM and its combination with HM and GF.
- To propose an optimal feature vector and classifier that provides a minimal error rate.
- To analyze performance of InfoGain based feature normalization technique.

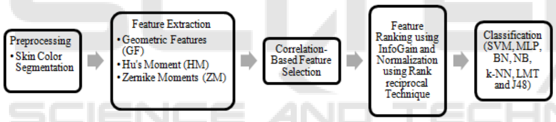

Figure 1: Proposed Framework.

2.1 Database

2.1.1 ISL Database

Figure 2 shows image data-set for 26 ISL alphabets. It is created for 90 subjects and has a total of 2300 images. The images are captured by a web cam of 15 megapixels, on a uniform (black) background, with varying illumination, at a fixed distance from the camera with a resolution of 640 x 480 pixels. ISL alphabets consists of 73% double hand signs. Use of double hand gestures results in hand-over-hand occlusion. Another challenge is imposed by signs having high similarity among themselves. These are the signs of alphabet 'E' - 'F', 'H' -'M' -'N', 'P -'Q' and 'S' - 'T'.

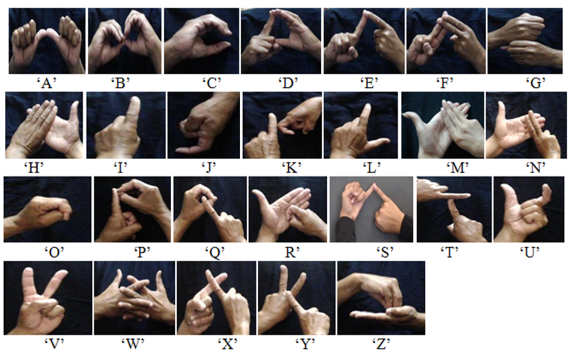

Figure 2: ISL Alphabets.

2.1.2 Treisch's Database

The proposed system performance is also analyzed on a standard Triesch's Database from the Frankfurt Institute for Advanced Studies. Images in light, dark and complicated background for 12 hand gestures, 20 subjects are used in the present study (Triesch and Malsburg, 2001).

2.2 Pre-processing

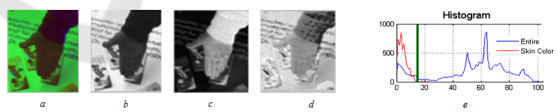

Figure 3: Skin Color Segmentation in Complex Background of Image from Treisch's Data-set a. Input Image b. 'L' color component c. Color component 'a' d. Color component 'b' e. Histogram of Skin and Entire Image.

Figure 4: ISL Alphabets H-M-N a. Without Internal Edge Details b. With Internal Edge Details.

Using skin color segmentation in preprocessing stage input colored images are converted to binary images. An effective skin segmentation algorithm must be capable of detecting skin colored pixels efficiently in the presence of light variations, shadows, and noise (Kakumanu, Makrogiannis and Bourbakis, 2007). The input RGB image is converted to Commission Internationale de l'Eclairage (CIE) Lab color model. Otsu's thresholding technique is clustering-based method and it works best for bimodal histogram characteristics. Therefore, it requires clearly distinguishable pixel values for hand and background. In Figure 3(e), it is observed that the 'a' color component has clear bimodal histograms. The ISL database has been acquired in varying light conditions. The effect of intensity variation are minimized if the intensity component is separated from the image. Lab color space separates 'a' and 'b' color component from intensity 'L'. Therefore, choice of Lab color space makes it invariant to light intensity also. So for pre-processing 'a' component of Lab color space is used here. To preserve the internal edge details of hand shapes, Laplacian of Gaussian (LoG) is used. Laplacian filter highlights the regions with rapid intensity changes and is highly sensitive to noise. To reduce sensitivity, Gaussian blurring is used and then Laplacian filter is applied. The pre-processed binary image includes the internal edges also. Figure 4 shows ISL alphabets 'H' -'M' -'N' without and with internal edge details. These signs have similar outer shape and can be distinguished only if inter edge information is added. Therefore, adding internal edge details helps to overcome the problem of hand-over-hand occlusion for double hand gesture.

2.3 Feature Extraction

Signs are represented as hand shapes. Recognition of SL can be defined as a linguistic analysis of these hand shapes. Shape-based features that can be used for shape recognition include Hu Moments (HM), Zernike Moments (ZM), edge information and Geometric Features (GF) (Mingqiang, Kidiyo, and Joseph, (2008)). Appearance-based feature vectors studied in this paper are summarized below:

2.3.1 Geometric Features

Geometric features are extracted for the binary hand images using region based parameters (area, moments and axis) and boundary parameters, the perimeter (Zhang and Lu, 2004).

- Circularity Ratio is a measure of the degree to which a shape differs from an ideal circle. It is found to be invariant to scaling, rotation and translation. The range lies between 0 and 1.

$$CR = \frac{Area_{Shape}}{Area_{Circle}} \tag{1}$$

- Spreadness is the measure of the spread of the shape. It is calculated using, the central moments.

$$SR = \frac{\mu_{20} + \mu_{02}}{\mu_{00} + \mu_{00}} \tag{2}$$

- Roundness is receptive to the elongation of image boundary. Roundness is equal to 1 for a circle. It has a less value for shapes other than a circle.

$$RO = \frac{4\pi Area}{Perimeter^2} \tag{3}$$

- Solidity describes the roughness of a boundary. Solidity is also equal to 1 for a region that has no concavities. It is the degree to which the shape is concave or convex. The solidity of a convex is 1.

$$S = \frac{AreaofShape}{ConvexHullArea} \tag{4}$$

- Average of Bending Energy (BE) is calculated by finding a magnitude of discrete Fourier transform, $|X_n(f)|$ of n boundary pixels. The boundary pixels of a shape are listed in a clockwise direction. Each pixel is represented as a complex-valued vector. The Parseval's energy relation is applied to find the bending energy. Circle has a minimum average bending energy.

$$BE = \sum_{1}^{n} |X_n(f)|^2 \tag{5}$$

- Eccentricity or the aspect ratio is ratio of the length of major axis (L) and minor axis (W) of the area covering the shape.

$$E = \frac{L}{W} \tag{6}$$

- Convexity is defined as the ratio of perimeter of the convex hull over that of the original contour of the shape.

$$CV = \frac{ConvexHullPerimeter}{ShapePerimeter} \tag{7}$$

2.3.2 Hu Moments

Hu Moments (HM) were proposed by M.K. Hu in 1962. HM are region-based invariant moments. These are translation, scale and rotation invariant. They represent the distribution of random variables and bodies by their spatial distribution of mass. The seven invariant moments are used as shape features. Consider a binary image as 2D density distribution function, here moments can be used to extract some properties of the image. For a binary image, regular moment m_{uv} of order u+v is given by "Eq. (8)":

$$m_{uv} = \sum_{0<x<=M-1, 0<y<=N-1} x^u y^v f(x,y) \tag{8}$$

From the "Eq. (8)", Hu derived seven set of moments with respect to rotation, translation, scaling and were computationally simple. First order moment locate the centroid of the image calculated using "Eq. (9)":

$$x_c = \frac{m_{10}}{m_{00}},\ y_c = \frac{m_{01}}{m_{00}} \tag{9}$$

To calculate the central moment centroid is subtracted from all the coordinates as given by "Eq. (10)". These moment then become invariant to translation.

$$\mu_{uv} = \sum_{0<x<=M-1, 0<y<=N-1} (x - x_c)^u (y - y_c)^v f(x,y) \tag{10}$$

Scale invariance can be obtained by normalization. η_{uv} are normalized central moments. These can be derived using "Eq. (11)"

$$\eta_{uv} = \frac{\mu_{uv}}{\mu_{00}^{\frac{u+v+2}{2}}} \tag{11}$$

The equations to derive seven Hu Moments listed by Sabhara *et. al.* (2013). It may be noted that Hu moments and Geometric features are un-normalized set of feature vector.

2.3.3 Analysis of Zernike Moments

Zernike Moments (ZM) are scale, rotation and translation invariant. Zhang and Lu (2004) reported ZM as one of the best choices out of several shape representation and description techniques. Sabhara *et. al.* (2013) reported ZM to be more accurate, flexible, and easier to reconstruct than HM. Also, increasing the order of the ZM increased the accuracy and as per the system requirement an optimal order of ZM could be chosen. Goyal and Walia (2014) applied ZMs as global features in achieving higher accuracy for region-based shapes in a Shape-Based Image Retrieval (SBIR) system. ZM are known as global shape descriptors. ZM are derived using orthogonal Zernike polynomial. These polynomial are a product of angular function and radial polynomial. The angular functions are the basis functions for the two-dimensional rotation group, and the radial polynomials are developed from the Jacobi polynomials. "Eq. (12)" is an expression for Radial polynomial R_{uv}. These are defined over interior of a unit circle, . V_{uv} is the orthogonal basis function of the image I(x,y), refer "Eq. (14)"(Khalid and Hosny, (2010)).

$$R_{uv}(r) = \sum_{s=0}^{\frac{(u-|v|)}{2}} \frac{((-1)^s (u-s)!)}{s!\frac{(u+|v|)}{2} - s!\frac{(u-|v|)}{2} - s} r^{(u-2s)} \tag{12}$$

If u is the order and v is iteration in polar coordinates.The condition that $u - |v|$ is even and $|v| < u$ is always satisfied. r is length of vector from origin to (x, y) pixel, θ is an azimuth angle between r and x axis in counter clockwise direction. It varies from 0 to 2π. u is positive integer or zero, v is positive or negative (Nallasivan, Janakiraman and Ishwarya, (2015)). ZM is given by "Eq. (13)":

$$ZM_{uv} = \frac{u+1}{\pi} \sum_{(x^2+y^2)<=1} I(x,y) V^*_{uv}(x,y) \tag{13}$$

Where V^*_{uv}, is complex conjugate of the Zernike basis function defined over the unit disk, derived using "Eq. (14)"

$$V_{uv}(x,y) = R_{uv}(r) e^{iu\theta}, r <= 1 \tag{14}$$

$$r = \sqrt{(x^2+y^2)}, r <= 1, \theta = tan^{-1}(\frac{x}{y}) \tag{15}$$

$$ZP_{even} = \sqrt{(u+1)} R_{uv} \sqrt{2} cos(v\theta) \tag{16}$$

$$ZP_{odd} = \sqrt{(u+1)} R_{uv} \sqrt{2} sin(v\theta) \tag{17}$$

Figure 5 show that even Zernike Polynomial is a cosine function and as order increases the number of zero crossings increases, thus enhancing the ability of ZMs to represent details within an image.

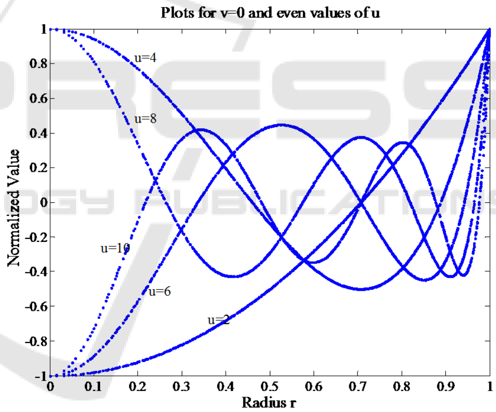

Figure 5: Zernike Polynomial plots for even values of u and 0th repetition.

Figure 6 shows the behaviour of Zernike polynomial for 10^{th} order and for increasing values of repetitions. The valid values of v for 10^{th} order are even values from 0 to 10. Observing the shapes of the curves in Figure 6, it is realized that as v increases, the curves becomes flat near the origin and are less oscillatory. This produces descriptions that the pixels lying closer to the perimeter of the unit disc will have more weight than those lying closer to the origin. Thus higher values of v are redundant in terms shape representing properties. Therefore, ZM feature vector including higher order and lower repetitions may prove useful. The highest value that v can acquire is equal to u.

2.4 Feature Selection and Normalization

In many classification problems, it is difficult to train classifiers before removing redundant features due to the huge size of the data. Reducing the number of irrelevant features reduces the running time of the learning algorithms and yields a more general classifier. Also ensures the better understanding of the data and the classification rule. Some machine learning algorithms are known to degrade in performance when faced with many irrelevant features. A set of selected feature must be derived for a particular dataset. Therefore, in this study an optimal set of features is extracted by using Correlation based Feature Selection (CFS). CFS selects the features having high correlation with the class and is not correlated with each other (Duch, Wieczorek, Biesiada *et. al.*, 2004). InfoGain (IG) is also known as mutual information. It is the gain in information or decrease in uncertainty of a class, when extra information is provided by attribute. The measure of uncertainty of class is Entropy, denoted as H(Y). H(Y/X) is entropy of Y conditioned on a particular value of X.

$$IG = \frac{H(X) - H(Y/X)}{H(Y)} \tag{18}$$

Once the selected feature vector is obtained, the ranking technique can find the feature listed in order of their priority. Feature rank is r_i (for i=1 to n),where, n is number of features. Feature weights are calculated using a Rank Reciprocal technique, such that sum of all the weights is 1. Each feature is multiplied by its corresponding weight. This results in feature normalization and now the feature vector values lie between (0 to 1), only. By applying Rank Reciprocal technique, weight w_i for each rank r_i is calculated by "Eq. (19)". This neutralizes the effect of different scales across features.

$$w_i = \frac{\frac{1}{r_i}}{\sum_{i=1}^{k} \frac{1}{r_i}} \tag{19}$$

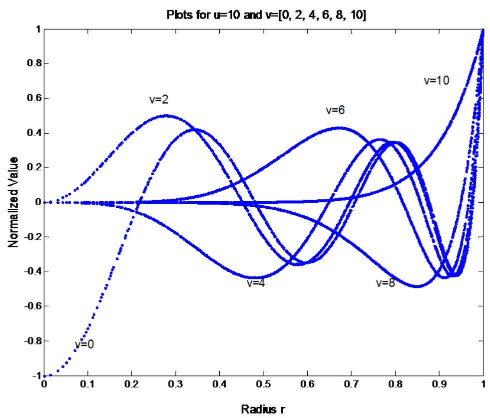

Figure 6: Zernike Polynomial plots for 10th order and all repetitions.

2.5 Supervised Machine Learning Techniques

SLR system is a multi-class classification problem with 26 classes of ISL alphabets. The classifiers considered in this paper are summarized here. Although, the Support Vector Machine (SVM) is a binary classifier, it can still be extended for multi-classification such as human activity recognition (Jakkula, 2011) and hence in SLR in this case. SVM is supposed to be effective in high dimensional spaces, in cases where a number of feature dimensions are greater than the number of samples. It uses a decision function called support vectors. Different kernels can be specified for the decision function. Penalty value, C can be from 0.01 to 100.The value of C=1 and a Polynomial kernel is chosen for this work. Multi-Layer Perceptron (MLP) with two hidden layer and back propagation based iterative method is used. Naive Bayes (NB) and Bayes Net (BN) are the statistical learning classifiers. These are also considered in this work. k-Nearest Neighbor (k-NN) is an instance-based learning. The value of k=3 and the Euclidean distance function is used to find neighbors. Several advantages of the decision tree as a classification tool have been pointed out in the literature. These are the non-parametric method. They tend to perform well if a few highly relevant features exist as compared to the case where complex interactions exist (Kotsiantis, Zaharakis, and Pintelas, 2006). In this study, J48 based on C4.5 algorithm and Logistic Model Tree (LMT), are considered.

3 RESULTS AND DISCUSSION

3.1 ISL Database

Table 2 shows the proposed feature vector for ISL database. In the case of ZM, MLP and SVM highest accuracy is around 89.5%. On combining ZM with HM and GF, a feature vector size of 135 is obtained. Highest accuracy of 92.7% is obtained for SVM and MLP. Next best performer is LMT with 91.2%. However, the concern with MLP is the time required to build the model when a feature vector is large. In terms of model building time, it is observed that SVM

Table 2: Results of Feature Selection and Normalization for ISL database.

Feature Vector	SVM	MLP	NB	BN	k-NN	LMT	J48
ZM(121)	89.4	89.5	76.5	74.7	81.1	87.7	79
Combined(135)	**92.7**	**92.7**	80.7	82.8	84	91.2	79.3
CFS (56)	**93.4**	93	89	87.3	86.8	92.1	80
Info Gain+ CFS (56)	96.3	96.7	**97.8**	96	89.7	96.3	86.3

performs better than MLP and LMT. For other classifiers accuracy remains less than 85%. In order to minimize the feature vector size, the standard CFS technique is applied to the combined set of 135 features. A reduced feature vector of size 56 is listed in Table 3. Among 56 CFS based selected features, there are 45 ZMs, 4 Hu Moments, and all Geometric features. Focusing on the ZM order, it is observed that 71% of selected feature vector are the lower order ZMs. Therefore, these results are in line with the generalized conclusions drawn while analyzing the behavior of Zernike Polynomial plots in section 2.3.2. It is worth noting that for selected feature set the performance of NB and BN improves significantly. Minor improvement is also observed in all other classifiers. Since the feature values have large variations. Therefore, normalization is done to bring the range of features within 0 and 1.For the normalized feature vector, the highest rise in accuracy is observed for NB, BN, and J48. Some improvement is also observed for SVM, MLP, k-NN, and LMT.

3.2 Triesch's Dataset

The proposed systems performance is also studied on standard Treisch's dataset. It has 12 signs of 20 signers captured in different backgrounds. The results are shown in Table 4. Three sets of Treisch‘s database are made. Set 1 includes images of all the signs in both uniform and complex background, Set 2 includes images of all the signs in uniform background only and Set 3 includes images of only 6 distinctive signs in uniform background. SVM gives higher accuracy in all the three cases. For uniform background and 6 distinctive signs, accuracy is 93.2%. It drops to 82.5% when all 12 signs are taken. The reason for this may be the large similarity among single hand signs. Accuracy dropped to 61.5% when images with complicated background are also included.

4 CONCLUSION

For ISL database, the accuracy of combined feature set, CFS based feature vector and normalized feature vector is compared in Table 2. For combined feature vector, MLP and SVM give the highest accuracy. It is worth noting that for selected feature set the performance of NB and BN improves significantly. Therefore, following specific conclusions are drawn:

- Among individual feature sets, ZMs are better than HM and GF. However, combining GF and HM enhances the performance of ZM.
- For higher orders of ZM, the feature vector size increases considerably while a significant improvement in accuracy is not achieved. Particularly in the case of Naive Bayes and Bayes Net it decreases due to the considerable increase in feature vector size.Therefore, a reduced feature set is obtained using Correlation based Feature Selection. In the reduced feature vector, 71% lower order ZMs. The value of iteration, $v <= 10$ are selected.
- For combined feature vector, SVM, Logistic Model Tree, and MLP show similar results and are better than other classifiers. The Logistic Model Tree performs at par with MLP and SVM for combined feature set. Therefore, it can be concluded that Logistic Model Tree, MLP and SVM are capable of handling the larger feature vector.
- For CFS based reduced feature set the performance of NB and BN improves while minor improvement is also observed in other classifiers. SVM performed best for reduced feature set. Further using InfoGain based feature weighing, the performance is enhanced. The major improvement is observed in the case of classifiers like NB, BN, k-NN, and J48, as these classifiers do not use an inherent feature normalization process. In case of normalized feature vector, NB outperformed SVM, giving the highest accuracy of 97.8%.
- In the proposed feature vector also contains some higher order lower order ZMs and the value of iteration, $v <= 10$ are selected. Therefore, going up to higher order and selecting the lower iteration value has resulted in an optimal feature vector.
- For Treisch‘s dataset, SVM gave a good accuracy for uniform background only.

The optimal shape-based feature set proposed in this paper shall further be integrated into a dynamic ISL recognition system. The proposed feature vector can be utilized directly for representing the hand gestures

Table 3: Optimal Feature Vector for ISL Database.

Feature Vector	Iteration (v)	Selected Features, ZM_u	No. of Features Selected
Zernike Moments (45)	0	$ZM_0,\ ZM_2,\ ZM_4,\ ZM_6,\ ZM_8,$ $ZM_{10},\ ZM_{12},\ ZM_{14}, ZM_{18}$	9
	1	$ZM_1, ZM_3, ZM_5, ZM_7,$ ZM_9, ZM_{11}, ZM_{17}	7
	2	$ZM_2, ZM_4, ZM_6, ZM_8,$ $ZM_{10}, ZM_{12}, ZM_{16}$	7
	3	ZM_3, ZM_5, ZM_7 ZM_9, ZM_{11}, ZM_{15}	6
	4	$ZM_4, ZM_6, ZM_{10},$ $ZM_{12}, ZM_{16}, ZM_{20}$	6
	5	ZM_7, ZM_{13}, ZM_{17}	3
	6	$ZM_{10}, ZM_{12}, ZM_{18},$	3
	7	ZM_7	1
	8	ZM_{14}	1
	9	ZM_{19}	1
	10	ZM_{18}	1
Hu Moments (4)	—	$H_1,\ H_2,\ H_3,\ H_4$	4
Geometric Features(7)	—	All Features	7
		Total Features	56

Table 4: Results on Triesch's Dataset.

Dataset	SVM	MLP	NB	BN	k-NN	LMT	J48
Set 1: Complex Background, 12 Signs	**61.5**	55.1	48.7	39.7	44.9	46.2	43.6
Set 2: Uniform Background, 12 Signs	**82.5**	80.8	60.3	58.6	61.1	78.2	56
Set 3: Uniform Background, 6 Distinctive Signs	**93.2**	91.4	85	83.8	79.8	92.3	81.6

in a cluttered background if the images are captured using depth camera. However, in future, the proposed system pre-processing stage shall be upgraded to work in the complicated background also.

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