Varietal discrimination of wheat seeds by machine vision approach

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Abstract: The main objective of this research was to investigate the potential of machine vision approach for the discrimination of five wheat varieties, *Aas, Bakhar, Farid, Miraj* and *Punjnad* with the implementation of statistical textural features extracted from bulk grain gray scale sample images acquired in absolute natural environment. By using MaZda software total 254 statistical features were extracted and an optimized set of 26, the most relevant features was obtained by merging the features selected by three statistical approaches, Fisher co-efficient (F), Probability Of Error + Average Correlation Co-efficient (POE+ACC), and Mutual Information Co-efficient (MI). These 26 features were deployed to Artificial Neural Network (ANN) for the discrimination of said varieties, and we received the accuracies 100%, 100%, 97.61%, 96.42% and 94.06% respectively.

[M. Shahid, M. S. Naweed, Salman Qadri, Mutiullah, E .A. Rehmani. **Varietal discrimination of wheat seeds by machine vision approach.** *Life Sci J* 2014;11(6s):245-252] (ISSN:1097-8135). http://www.lifesciencesite.com. 46

Key Words: Textural features. Artificial Neural Network. Wheat Varieties. Mazda software

1. Introduction

Seed selection of food crops like; wheat, maize, rice etc., is performed under three main objectives i) to have maximum yield under specific environmental factors like, field fertility, water requirement and climate conditions, ii) seeds with better nutritional contents (food values) and, iii) better disease immunity. The specific seed may be selected by discriminating a variety of seeds of a crop. Up to now, it is being performed by skillful experts who discriminate the varieties on the basis of visual assessment. A trained personal involves qualitative parameters, like shape, color, size, and physical kernel texture, which are subjective and affected by individual's experience.

According to Anami and his coauthors, the decision making capabilities of an expert can be seriously affected by his/her physical conditions such as fatigue, eyesight, work pressure and working conditions [1]. Moreover, an expert may not be familiar with a newly launched variety. Transportation of seed samples to an expert is also a time consuming procedure. Hence, an objective approach, like machine vision, will help to reduce the subjective nature of this assessment method and will save the time as online image handling requires no time.

Recently, machine vision employing image processing is being used very successfully to characterize the complex shape, size and texture quantitatively, for example Dubey and his co-authors classified three varieties of wheat on the basis of 45 morphological parameters extracted by this method and achieved an accuracy rate from 84% to 94% for individual wheat varieties by the implementation of Artificial Neural Network (ANN) [2]. Similarly, seed discrimination of five Canadian wheat varieties was performed by Majumdar and Jayas by using 23 morphological features and the authors reported an average classification rate of 98% [3]. In the same, way discrimination of five cultivars of durum wheat varieties was performed by Farahani on the basis of 11 morphological features and achieved an average 67.66% accuracy [4]. Arefi et al. also performed discrimination of four Iranian wheat varieties on the basis of color and morphological parameters, and achieved an average 95.86% accuracy in their results.[5] Color and morphological features have also been used by Choudhary et al. and Chen et al. for the same purpose very successfully [6-7].

Dubey et al. used total 600 grains (200 grains from each variety) and a total number of 31500 kernels were used by Majumdar and Jayas to extract the said parameters [2,3]. It is worth to be noted that morphological features are extracted per kernel basis, hence, arrangement of such a huge number of kernels in a specific orientation under an imaging device, and then extraction of parameters is an exhausting and time consuming procedure.

Some researchers also tried to investigate the impact of different illumination conditions on the discrimination analysis of grains. To discriminate five cereal grains Paliwalet et al. used a ring shaped fluorescent tube light for image acquisition and reported 96% accuracy when an optimum set of morphological, color and textural features were used by applying a four-layer back propagation neural network classifier [8]. Similarly effect of three type of illumination sources were compared by

Manickavasaganet et al. in the discrimination of eight Western Canadian wheat classes [9] and the highest classification rate of 96% was obtained with the similar light source as reported in Ref. (fluorescent tube light) [8].

Intensity variation among the pixels also reveals useful information. The gray-level variation within the image quantifies the textural features of the objects in that image. According to Bharati et al. to extract textural features on the basis of gray-level variation four methods [10]; stochastic, statistical, structural and spectral are commonly used. Depending on the number of pixels which define the local features, statistical methods further can be divided as, first-order, second-order and higher-order statistics. First-order statistical textural features are related to the intensities of individual pixels independent of the neighboring pixels, where as the joint probability distribution of pixel values is called second-order and higher-order statistical approach. Statistical approach is the best method to extract textural features when these features are evenly distributed throughout the image. So, a number of investigators used this method for the identification of seeds other than morphological and color features.

Zapotoczny, identified five Polish varieties of spring barley by using texture parameters in different color channels [11]. Statistical textural parameters were extracted in two modes, per kernel basis and for the bulk of grains. An error rate of more than 50% is reported when classification was performed per kernel basis and it reduced to less than 1% when applied for bulk, and an average identification rate of 99.22% was obtained. In another work with the help of statistical textural features derived in different color channels, discrimination of 11 wheat varieties was performed by Zapotoczny [12]. The features were extracted from images of single kernel, 10 kernels and 20 kernels of each variety and an average accuracy more than 90% has been reported, when analysis was performed on the basis of 20 kernels.

Douik et al. used morphological, color, and wavelet features to discriminate three types of cereal grains [13]. A total number of 152 parameters (122 morphological, 18 color, and 12 wavelet) were extracted from 3000 grains (1000 grains from each variety) and with the implementation of *ANN* classification method an average accuracy of 98% was achieved.

By using statistical parameters along with *Local Binary Patterns (LBP), Local Similarity Patterns (LSP),* and *Local Similarity Number (LSN),* nine Iranian wheat varieties were classified by Pourreza et al. from the bulk sample images [14]. An optimum set of 50 features (23 statistical and 27 features from all other mentioned approaches), was selected by using *Linear Discriminant Analysis (LDA)* classifier. The investigators reported that gray-level features showed the highest identification accuracy as compare to the other mentioned groups of features. By using hybrid feature model an average classification rate of 98.15% was obtained.

Wheat and barley kernels were classified by Hernandez & Gil with the implementation of total 99 statistical, color, and morphological features [15]. A total number of 545 grains were used for this work and features were extracted from each kernel. Out of these 99 features, 72 were statistical and only 27 features belong to all other types. An accuracy of 99% was claimed by the authors.

Bulk samples of five types of grains named; barley, oats, rye, wheat and durum wheat were analyzed by Visen et al. by using color and textural features [16]. The images were acquired in laboratory arrangement. Total 179 (color and statistical features) were extracted, which were reduced to 40 (20 color and 20 statistical) by using back propagation Artificial Neural Network. An average classification accuracy of 98% is reported with this combined set of features.

Literature survey revealed that the most of the research work in the field of grain identification and discrimination has been performed in a controlled or laboratory environment. All the researchers cited above used a specially arranged setup (to develop ideal conditions) for the extraction of morphological, color and other textural parameters, which is a cumbersome procedure. Moreover the algorithms which use morphological and color parameters (based on the images of individual grains) for the seed classification require a number of pre-processing operations such as, segmentation, background removal and object extraction, which are lengthy and time consuming.

The aim of this work was to develop a simple, concise and robust method for the extraction of textural parameters to differentiate five wheat classes, in an absolute natural environment. To avoid complex laboratory setup for the extraction of morphological and color features, we used only statistical textural features in this work and an excellent result with an average accuracy of 95% was achieved

2. Material and Methods

2.1 Samples and Image Acquisition

Five wheat varieties; *Aas, Bakhar, Farid, Meraj,* and *Punjnad* (2Kg of each variety) were used in this work. The said samples were obtained from the Agriculture Regional Research Centre Bahawalpur Region, Punjab, Pakistan. Images were acquired by a digital camera of Company; Nikon, model Coolplex having a resolution of 10.1 megapixels. To record the light intensity at the field a digital luxmeter (MS 6610, MASTECH) was used. For image acquisition the sample grains were put in a tray having dimensions 2.5×1.5 ft. under the camera at a normal distance of 10 ft. in bulk form. As the statistical texture analysis approach is best suited for fine textures so to meet the conditions this height was selected. To avoid the inter grain shadow effect the imaging was performed at noon time (12.00 pm to 2.30 pm) under clear sky and 25 images of each variety were acquired according to following scheme (Table 1).

Table 1. Time and Intensity Information

Sr. no	Variety	Time	Light Intensity
1	Aas	12.00 pm	29400 lux
2	Bakhar	12.30 pm	29265 lux
3	Farid	1.30 pm	28641 lux
4.	Miraj	2.00 pm	25329 lux
5.	Punjnad	2.30 pm	24200 lux

To change kernel configuration the sample was shaken after each camera shot and a wooden ruler was used to remove the humps and pits on the sample surface.

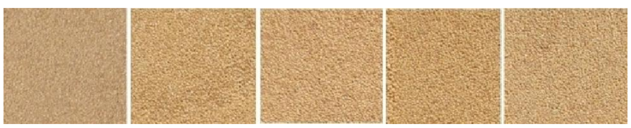

Fig. 1 Samples of *Ass, Bakhar, Farid, Miraj and Punjnad*

In this way total 125 (25×5) colored images with the dimensions 2736×3648 pixels and 24 bits depth having jpg format were obtained, but for this work perceptually the best 21 images from each variety were selected.

2.2 Preprocessing

Each image had a vast unwanted surrounding area, which was removed by cropping the sample relevant portion from each image. Sample images having dimensions 300×200 pixels were obtained from each image. The cropped images were converted to gray scale by using IrfanView software and were stored in bitmap (bmp) format, because the software MaZda, which was used to calculate texture parameters/features, only works for this format [17].

To increase the sample data set 14 non-overlapping sub-images or regions of interest (ROIs), were developed in each image. In this way a data set of 1470 images was obtained.

2.3 Image Analysis and Classification

Image analysis and feature extraction were carried out by MaZda version(4.6) software, and a set of 254 statistical texture parameters were calculated. The calculated parameters may be grouped as: 9 histogram features which are known as first-order statistical parameters, 5 Auto regression parameters, 220 (11×4×5) second-order statistical parameters, derived from *Gray Level Co-occurrence Matrix (GLCM)*, which consist of 11 Haralick parameters calculated in all directions (0^o, 45^o, 90^o and 135^o) up to 5 pixel distance [18], and 20 (5×4) higher-order statistical parameters derived from *Gray Level Run Length Matrix (GLRM)*, which also consist 5 parameters in all directions like *GLCM* . In this way each *ROI* was defined by 254 textural features, and statistically it means that the data was presented in 373380 (1470×254) dimensional features vector space.

It is worth to be mentioned here that all of the 254 calculated features were not equally important for seed discrimination. Moreover, statistically a huge data is required to have a reliable discrimination and classification results on the basis of so large number of features, which is not generally available. So, it was necessary that feature vector space dimensionality should be reduced by selecting the most relevant features which have the ability to discriminate and classify the different seed classes.

Following three supervised feature reduction methods; *Fisher Co-efficient (F) Probability Of Error + Average Correlation Co-efficient (POE+ACC)*, and *Mutual Information Co-efficient (MI)* available in MaZda software, were adopted for the selection of the most appropriate set of features [18]. For each features selection method this software selects the 10 most significant features and presents these features in descending order according to their significance. In this way total 30 (10 features by each mentioned method) were selected. As the combined set of features gives better classification results hence, all the above mentioned 30 features were merged together. Because 4 features were common, in this way an optimum set of 26 features was obtained for final procedure.

For the purpose of data analysis and classification a program B11 was used, which is integrated with MaZda software. But, prior to classification the features data was standardized to reduce the effect of unwanted variation within the features values due to outliers and other artifacts by applying the following mathematical relation:

$$x_j' = \frac{x_j - \bar{x}}{\sigma}$$

Where: x_j'— is the standardized value of jth feature and j= 1, 2, 3, 4, …….. n,

x_j — Original feature value

$\bar{x}$ — Mean feature value

σ — Standard deviation.

The above mentioned approaches of feature selection *(F, POE+ACC, MI*), only select the most significant parameters, but do not directly express the degree of texture discrimination power. To evaluate the varietal discrimination/classification and data clustering the selected 18 featured data was deployed to non-linear discriminant analysis *(NDA)* (available in B11 software), Materka et al. have already proved that *NDA* approach gives the best results for combined or hybrid parameters.[19],.

The following two methods of supervised classification are available in B11: *1-Nearest Neighbor (1-NN) and Artificial Neural Network (ANN). ANN* classifier was implemented because; firstly we have supervised data (due to five seed varieties) secondly according to Park et al. *ANN* is a robust approach for noisy and incomplete data (such factors are always present in data set acquired in natural environment) [20]. For varietal discrimination the finally selected 26 features were deployed to *ANN* classifier. The architecture of proposed classifier was as under:

Input layer: 26 nodes, (equal to input parameters)

Hidden layer: 10 neurons, (maximum limit of software)

Output layer: 5 nodes, (equal to varieties to be classified).

Statistical data of total 1470 bulk sample sub-images (294 ROIs of each variety) was deployed to *ANN* classifier in this work. For training a data set of 1050 sub-images (210 ROIs from each variety) and for testing a data set of 420 (84 ROIs from each variety) was utilized.

3 Results

In first attempt varietal discrimination and data clustering was verified on the basis of features selected by *F, POE+ACC* and *MI* approaches for the ROI (8x8) size, but, the results were unsatisfactory when the selected features by each approach were deployed to NDA classifier individually, due to very poor classification rates of 64.23%, 61.78% and 67.19% respectively. To have better results, we merged all these above mentioned features and received an average classification of 61.760%, which was not still an acceptable result. Then the same procedure was adopted for ROI (16x16), and we received a classification of 74 .21%, 77.33% and 79.44% respectively for individual sets of features and 91.04% when the features were combined. Still the output was not satisfactory because of high misclassification rate of more than 9.96%.

ROI (32x32) size was tried as third attempt and we received excellent results, when a combined set of 24 statistical textural features was deployed to *NDA* classifier, with a classification rate of 96.69%. But, when these results were implemented for the testing of data samples an average discrimination rate of 93.23% was received, which was also rejected due to poor performance.

In the last attempt ROI (64x64) was tried to have required results. When the individual sets of features, for this size of ROI, selected by above mentioned approaches *(F, POE+ACC, MI)*, were deployed to *NDA* classifier, an average accuracy of 93.25%, 90.74% and 93.655% respectively was achieved. As mentioned above all these features were merged together, in this way a set of 26 features was obtained. When this combined set of 26 features was implemented, the best discrimination result of 99.82% was obtained, and all the classes were duly clustered fig.6, with the same *NDA* classifier, hence we used these features for further procedures in this work.

AS it is already mentioned that for system training 1050 ROIs were deployed to ANN. We received an average accuracy of 99.81% when the said data set was implemented under the n-class training option to train the system

During training phase only two samples of *Punjnad* were misclassified as of *MIraj*. To test the performance of these results, above mentioned 420 sub-images were deployed to *ANN* classifier under the option, n-class testing, and an average accuracy of 97.38% was received.

In testing *Aas* and *Bakhar* were 100% classified, 3 samples of *Farid*, were reported as belong to *Bakhar*, 4 samples of *Miraj* were misclassified as, 2 of them belong to *Bakhar* and other 2 belong to *Punjnad* and 4 samples of *Punjnad* were misclassified as belong to *Miraj*.

Miraj and *Punjnad* were highly misclassified in each ROI size analysis as compare to other three varieties. It might be either due to higher inter grain shadow effect at 2.30pm as compare to 12.00pm or low light intensity recorded by luxmeter, which was 29400 lux at 12.00PM and 24200 lux at 2.30PM.

Table: 2 Feature for ROI (8x8)

F	POE+ACC	MI
Contrast (1,0)	Correlation (5,-5)	Contrast (1,1)
Diff. Entropy (1,0)	Correlation (4,4)	Contrast (0,1)
Diff. Entropy (1,-1)	Sum Avg. (0,5)	Diff. Entropy (1,0)
Diff. Entropy (0,1)	Θ_2	Entropy (1,0)
Entropy (0,1)	Gr. Skewness	Contrast (1,-1)
Entropy (1,0)	Correlation (0,2)	Diff. Entropy (0,1)
Contrast (0,1)	Correlation (4,0)	Diff. Variance (1,0)
Variance	Skewness	Diff. Variance (1,-1)
Gr. Mean	ASM (5,5)	Entropy (0,1)
Contrast (1,-1)	Diff. Entropy (1,1)	Diff. Entropy (1,-1)

Table: 3 Feature for ROI (16x16)

F	POE+ACC	MI
Diff. Entropy (0,1)	Correlation (2,-2)	Diff. Entropy (1,-1)
Diff. Entropy (1,0)	Correlation (4,0)	Diff. Entropy (0,1)
Diff. Entropy (1,-1)	Correlation (5,5)	Entropy (1,0)
Entropy (1,0)	Correlation (0,5)	Entropy (0,1)
Entropy (0,1)	Correlation (5,-5)	Entropy (1,-1)
Entropy (1,-1)	Sum Avg. (5,5)	Inv. Of Moment (1,0)
Inv. Of Moment (0,1)	Contrast (0,1)	ASM (0,1)
Inv. Of Moment (1,0)	Entropy (0,1)	Diff. Variance (1,-1)
Contrast (0,1)	Gr. Kurtosis	Contrast (0,1)
Gr. Mean	Θ_1	Contrast (1,-1)

Table: 4 Feature for ROI (32x32)

F	*POE+ACC*	*MI*
Parc.99%	Correlation (2,2)	Entropy (1,-1)
Sum Entropy (3,0)	Correlation (5,5)	Contrast (1,-1)
Contrast (3,-3)	Correlation (5,-5)	Inv.Dif.Mom (1,-1)
Contrast (2,-2)	Correlation (0,4)	Inv.Dif.Mom (2,-2)
Sum Variance (2,2)	135^oLng.Rmph.	Sum Variance (2,2)
Sum Variance (4,0)	Perc. 50%	Dif.Entropy (1,-1)
Sum Variance (3,0)	Dif.Variance (1,-1)	Dif.Entropy (2,-2)
Inv.Dif.Mom (0,1)	Gr. Kurtosis	135^o Fraction
Inv.Dif.Mom (1,-1)	Θ_4	Dif.Variance (1,-1)
Dif.Entropy (0,1)	Contrast (1,-1)	Sum Entropy (4,0)

Table: 5 Feature for ROI (64x64)

F	POE+ACC	MI
Sum Enropy (3,0)	Correlation (5,-5)	Entropy (0,1)
Diff. Entropy (1,-1)	Perc. 50%	Entropy (0,2)
Sum Enropy (4,0)	Θ_4	Entropy (3,0)
Sum Enropy (2,2)	Correlation (0,5)	Entropy (1,0)
Perc. 99%	Correlation (5,0)	Diff. Entropy (1,-1)
Diff. Entropy (2,-2)	Correlation (5,5)	Sum Enropy (4,0)
Diff. Entropy (1,1)	Correlation (2,-2)	Contrast (1,-1)
Sum Variance (4,0)	Gr. Skewness	Contrast (2,-2)
Entropy (1,-1)	Contrast (1,1)	Perc. 50%
Entropy (3,0)	Entropy (3,0)	Correlation (2,-2)

4. Discussion

In this work bulk sample images are used like Zapotoczny who also used same type of images and achieved 99 % accuracy, but he analyzed 24 bit images in four color channels by using a combined set of wavelet and statistical textural features, which requires more computational time and storage capacity, whereas we have received an average classification of 97.38% by analyzing 8 bit gray scale images with the implementation of only statistical parameters, which requires comparatively smaller time [11],. Similarly some other researchers like Granitto, Farahani, Kannur Visen , Douik and his co-author Arefi and Shantaiya performed the seed discrimination and reported an average accuracy of 99%, 67.66%, 84.83%, 85%, 98%, 98%, 95.86% and 84.83% respectively, on the basis of morphological, color and textural features, as earlier mentioned in introduction , to find morphological parameters a number of preprocessing procedures are required, but in this work no such complicated procedures are adopted [4, 5, 13, 16, 22, 23].

In the same way Pourreza et al discriminated the nine wheat varieties by using statistical, *LBP*, *LSN* and *LSP* parameters extracted from bulk wheat sample images and achieved 98.15% accurate results [14], and here in this research we used only statistical parameters to have our aim. This makes our approach easier, less time consuming, robust and efficient to discriminate the given wheat varieties.

Table 6. Confusion table for the Classification Results ROI (8x8)

	Aas	Bakhar	Farid	Miraj	Punjad
Aas	203	7	0	0	0
Bakhar	2	193	5	2	8
Farid	3	2	189	8	8
Miraj	6	5	3	196	0
Punjnad	20	13	20	30	127

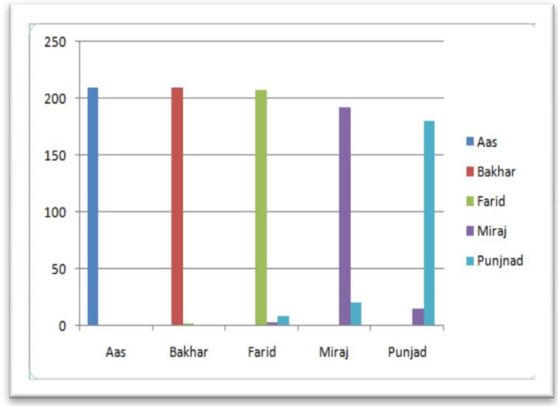

Figure 2 Classification results for (8x8)

Table: 7 Confusion table for the Classification Results ROI (16x16)

	Aas	Bakhar	Farid	Miraj	Punjad
Aas	210	0	0	0	0
Bakhar	0	210	0	0	0
Farid	0	2	201	7	10
Miraj	0	0	8	183	19
Punjnad	1	3	13	21	172

Table: 8 Confusion table for the Classification Results ROI (32x32)

	Aas	Bakhar	Farid	Miraj	Punjad
Aas	210	0	0	0	0
Bakhar	0	210	0	0	0
Farid	0	4	206	0	0
Miraj	0	3	0	204	3
Punjnad	0	2	0	4	204

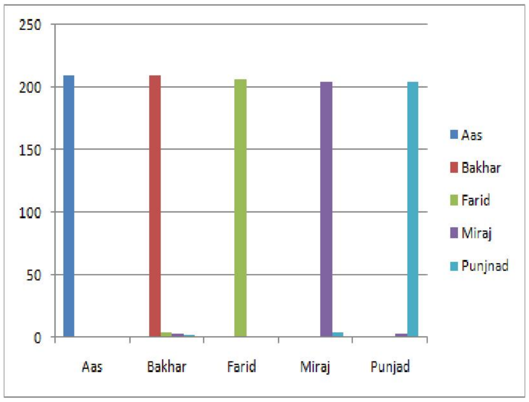

Figure 3. Classification results for (16x16)

Figure:4 Classification results for (32x32)

Table: 9 Confusion table for the Classification Results ROI (64x64)

	Aas	Bakhar	Farid	Miraj	Punjad
Aas	210	0	0	0	0
Bakhar	0	207	3	0	0
Farid	0	2	203	2	3
Miraj	0	2	0	199	9
Punjnad	0	4	4	6	196

Figure.5 Classification results for (64x64)

5. Conclusion

In this work five wheat verities were discriminated on the basis of quantitative parameters rather than, conventional qualitative parameters and an average accuracy of 97.32% was achieved.

As bulk grain sample images were used to extract said quantitative parameters, hence a number of pre processing procedures, like background removal and segmentation etc., were not required.

Only statistical textural features (26 parameters) were implemented for the analysis of images which made our approach faster than the other approaches in which morphological, color, and other textural features are used.

Artificial Neural Network (ANN) was implemented very successfully for the discrimination of five wheat varieties *Aas, Bakhar, Farid, Miraj* and *Punjnad* with an accuracy of 100%, 100%, 97.61%, 96.42% and 94.06% respectively.

In future the effect of light intensity and effect angle of incident light will be verified.

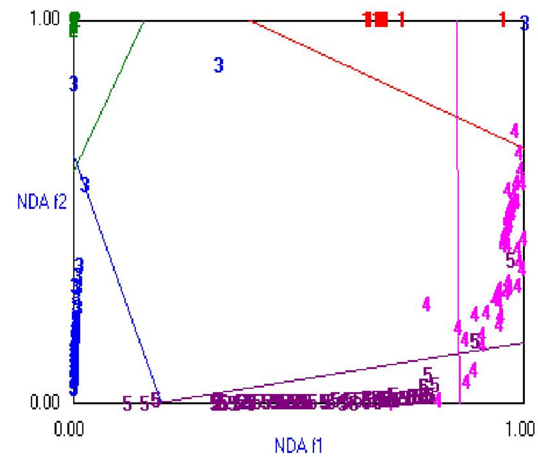

Figure 6. Data Clustering ROI (64x64) with NDA classifier

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4/12/2014