An Enhanced Feature Extraction Model for the Information Retrieval In Crop Disease Detection

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ABSTRACT

Feature Extraction in image processing has more significance in a large-scale development process. Semantic hashing is an efficient way to accelerate similarity identification process in the Computer Aided Detection (CAD) system. The organization of CAD system is highly application dependent. Some systems are stand-alone applications which solve a specific measurement or detection problem. The evolution of CAD system has made a giant leap in the effective detection. Furthermore, it can help to get better sensitivity, cost effectiveness and less time-consumption. After completing the region identification process, the feature extraction evolves the significant architecture to accumulate the classification process. In this work, an enhanced feature extraction model is developed by using the component analysis which merges the various set of features to produce the effective implementation of the classification.

Keywords: Color Correlogram, Color Moment, Spectral Hashing, Semantic hashing.

I. INTRODUCTION

The precision agriculture technology is designed to monitor the crop and soil conditions electronically with the assistance of various technological development. The adoption in the PA technology and its diffusion of innovation is validated by using the IS theory. The compatibility, quality of support, knowledge derivation, perceived usefulness of the PA technology and it's attributed, impact with its decision model are assessed as the context of PA. The policies for the standardization and coordination of the significant entities are validated with its implication.

In the application of remote sensing in the PA with the geospatial technologies and its corresponding sensors and described by Chunhua et al, 2012. The approach mainly perform the low cost operation in environmental monitoring by using the Unmanned Aerial systems (UAS). This system operated with high spatial and temporal resolution in the image acquisition process. The UAS system applies the zonal mapping as a key component to fetch the accurate information about soil and corp. the UAS primarily validated for the platform reliability, sensor capability, initial cost and maintenance cost to retire the large volume of data.

The relevancy of the PA in the whole vineyard scale was analysed by Santesteban et al, 2013. The precision viticulture is applied in the field level to retrieve the variability in the "Within a field" image with high resolution. The spatial variability is determined by estimating the NDVI factor in the captured image. The soil apparent conductivity and elevation are the environmental factor which characterizes the spatial variability and its responses. The significance of the agronomic was tested by comparing the environmental factor in three-level classification. The images illustrated the implication in both agronomic and oenological was defined with

high resolution images. The identified spatial variation is mainly associated to elevate the quality and its significance.

II. RELATED WORK

The ideal features of the images extraction and representation in the image vision is reviewed by Dong Ping Tian (2013). The image features such as colour feature, texture feature, shape feature, histogram, correlogram, and edge are illustrated with its representation as segmented region and tree. The development of virtual image representation organized into region detection, feature extraction and vector quantization. In each segment region, possible set of image features are extracted and represented in the form of tree.

Feng Cheng et al (2012) illustrated the computational accelerator for the feature extraction in real time images. The techniques is mainly based on the Scale Invariant Feature Transformation (SIFT) to derive the available features. The SIFT reduces the memory requirement by incorporating three stage pipeline in parallel architecture. The method is operated in four stages:

1. Gaussian-filtered and Difference of Gaussian image building.
2. Identifying the key point with stability checking.
3. Calculating the principle orientation.
4. Generating the feature descriptor.

The local feature detection algorithm (zhan et al, 2014) using the SIFT is employed for object recognition. This scheme is applied for ubiquitous access in the cloud computing environment by enabling the image computing. The process of privacy preservation is achieved with a feature descriptor in both magnitude and direction computation. The system has been designed with two generators with dummy identified to fill the comparer before loading or storing the image from the private cloud, the image content is encrypted using the public key homomorphic algorithm. And the generator utilizes the scale space cube generation which performs the convolution and subtraction using the SIFT algorithm. The significance of image descriptor is identified with the help of Gaussian function over the plain text domain. Cube permutation and noise perturbation are over lapped to encrypt the image features using cube encryption. Key point discovering and descriptor decryption is applied to decode the enciphered data into plain text information.

The feature extraction is unsupervised manner in the images captured during the remote sensing was represented by Adrrana et al (2015). The author proposed the greedy layer wise unsupervised pertaining to handle the sparse features in the images. The process takes the images in the form of multi spectral and hyperspectral imagery. These process are evolved in the deep convolutional architecture using deep network with sparsity. Instead of identifying the local minima using the fine-tuning process, enforcing population and lifetime sparsity is used in unsupervised learning with potential. The pertaining process is applied in greedy layer wise with discriminative feature learning. Essentially, the stochastic gradient descent with adaptive learning rate is optimized to recapitulates the spare target features.

The recognition of images based on the extracted features are review in the survey performed by Gaurav Kumar et al (2014). The feature extraction phase is applied after completing the binarization, thresholding, resizing and normalization process. The geometric conclave, convex parts, number of endpoint branches, joints are the local features and these are termed as the structural features. The topological features including the connectivity, projection profiles, number of holes and the linear invariant moment in the form of statistical features are represented in both micro and macro features of the images. The grayscale properties such as entropy, threshold and number of black pixel are used to differentiate the contour of the discriminating images. The encoding pixels including the crossing and distances, global transform and the series expression with linear combination are used to generate the one

way representation. The arithmetic computation absolute value operation, Fourier transform, wavelet transformation with high resolution, Eigen vector analysis, normalization of moment the primitive process in the feature extraction phase.

Zisha at al (2015) integrates the methodology for feature extraction with tensor discrimination analysis to handle the redundant information and subsequent classification process. The solution is based on the Gabor filtering to preserve the structure information with parameter setting. The feature tensor generates the row-wise and column-wise orientation based on the wavelet. The correlated structure information is used to eliminate the redundancy of the feature with similar strategy. The Local Tensor Discriminant Analysis (LTDA) is derive the second order feature with low dimension tensor. The reduction is automatically operated in optimal manner. The reduced feature tensor builds the vector representation using the quantization process. The rearranging process is effectively utilized to extract the vector representation from the feature representation with discriminative features. The Gaussian kernel is adopted by cross validation using the classification process in the SVM regularization with the multi-class input.

Wenzhi et al (2016) proposed the classification methodology based on the classification methodology based on the spectral-spatial features in the dimension reduction using deep learning process. The author develops a framework by using the balanced local discriminant algorithm with embedding technology to extract the features by stacking the spectral and spatial relationship. In the image classification process, multi feature based classifier is used with training process. The Convolutional Neural Network (CNN) is utilized with the structural and contextual information of the image in spatial domain. The dimension reduction is evolved by performing the Principal Component Analysis (PCA) feature with the coordinated reference data to derive the deep features of the image. The framework combines the spectral domain and spatial domain features to train the CNN

in both geometrical and discriminate structures, the affinity matrices of the images are formed with heat kernel parameter which maximizes the local margin of the input sample. This trained sample significantly achieves the better performance in the classification process.

The top hat transform for the featured extraction in the multi-scale image was suggested by Xiangzhi et al, 2012. The multi-scaling process is employed to differentiate the bright and dim regions by using the structured elements with the same shape and increasing size. The structural element pixel values are handled by enlarge the contrast in pixel extracted feature. The performance of image is validated by checking the PSNR, clarity of the image against the noise condition as the linear term index of fuzziness. The internal regions extracted from the multiscale image is operated for the large gray vales of all scales to determine the available features in the image region.

The colour occurrence method with the colour extraction was suggested by Sachin et al for digital images. The smoothing filter was used with the histogram equalization in the pre-processing stage of images. The intensity values are distributed by the cumulative distribution function for the gray image in the colour enhancement phase. The boundary and the spot detection algorithm is applied in the converted HIS model of the image to identify the possible combination of region present in the image. The image objects are classified by K-mean clustering and Otsu - Threshold process by taking the segmented region as input. The learning based object classified is applied with the help of back propagated neural network which classifies the recognized colours of the disease leaf.

The colour inverting model using the dehaze algorithm and adaptive region based method was studied with face recognition based application. The optimization algorithm in the image processing and histogram equalization methods are considered for the computation of high dynamic image processing techniques.

III. FEATURE SELECTION PROCESS

The feature is defined as the point of concern for image description. In computer vision and image processing the feature entity is used to represent a piece of data entropy which is crucial for resolving the computational task affiliated a particular application. Features can concern to the consequence of a general locality cognitive operation as feature extractor or feature detector applied to the image, specific structures in the image itself, ranging from the structures such as points or boundaries to the more composite structures such as objects. Feature Extraction is used for extracting the important data from the Entire data. It is a type of multi-dimensional simplification that efficiently represents concerning components of an image. Feature extraction is very dissimilar from Feature selection, the feature extraction consists of translating an absolute data, such as images, into quantitative features. This process is a machine learning technique which is applied to derive the important components of an image.

Component Analysis seeks to decay a multivariate signal into the amount of autonomous non-Gaussian points. The Color Autocorrelogram method takes out the Color correlative entropy from the color correlation feature matrix as a modern characteristic signifies and aggregates Correlogram to generate a composite characteristic. The foregrounds of this component feature is to include spatial correlation with relativity, circular distribution of localized connectivity relationship of colors.

IV. ENHANCED FEATURE EXTRACTION

Color AutoCorrelogram is a methodology which processes the image and generates the output with m×m feature vectors. Despite the circular distribution of the localized relativity of colors, it takes a high execution time and memory space for such large vectorized representation. Color Autocorrelogram only evokes the entities of the extending oblique in the feature matrix to represent the vectored feature, that outcomes the linear connectivity relationship of similar colors. While Color Correlogram conveys another pairs of colors in the spatial dispersion, and its utilization has been bounded by large feature vectors in covering with image equalizing. Simplified form of Color Autocorrelogram crisply deducts the computational complexity, and the recovery efficiency of the image with loaded colors or impressive variation in colors is not pretty good because only similar pairs of colors have been considered. Color correlative Information based on the Color Correlogram feature matrix, which not only abbreviates the feature vector to one dimension with m elements, but also encloses spatial entropy of another matches of colors.

The function of this signifier is to represent the spatial information about colors by pixel connectivity correlations at various spaces. It estimates the chance of identification in the image for two pixels with color C, at a particular distance d from each other. For each distance d, m probabilities are estimated, where m represents the number of colors in the normalized space. This extraction method incorporates the autocorrelogram for more number of image properties. The properties considered are: contour, magnitude of slope (variation), grade of a pixel point (rank), and texturedness. The Color feature is extracted in RGB color model and the other properties are identified from the gray scale level of the image.

Color Moment represents the color distribution of the image in the discrete form in color vectors. Shifting of input data is accomplished by means of the Region of Interest (ROI) into the collection of necessary features for categorization. The features expressed and suggested must be carefully chosen, because it is awaited to execute the demanded assortment task by applying the concentrated internal representation alternatively to complete ROI. Functioning with sufficient quantity of entropy information is commonly demanded a heavy amount of storage and computational power or an assortment algorithm which accommodate the input training data. The

characteristics derived from the first order textural characteristics, next order slope features, Discrete Wavelet Transform features using HAAR transform. In order to identify the color moment, the segmented image has been divided into number blocks of 4×4 picture elements and a lineament vector for each block which consists of 6 elements that has been extracted from the image. The LUV color space has been used where L stands for luminance, U stands for hue and V for saturation, U and V contains color information in the form of distribution which includes the chrominance. These LUV are the mean value of the Luminance, Hue and Saturation, respectively, which is represented in the form of 16 pixels and displayed as the 4×4 blocks. For the other features HAAR (wavelet) transform has been used for the composition of the image. After completing one-level wavelet transform, a 4×4 block is decomposed into 4 frequency bands of 2×2 block. The other elements of each feature vector are the straight root of second order moment that is in the form of wavelet coefficients.

Color Histogram is the oldest method to represent the feature, which is differed to rotational alteration, changes in the distance and incomplete resolution of the target object. The histograms are basically divided into pixel in an attempt to coarsely constitute the capacity and to reduce dimensionality of the resultant equalizing stage. A feature vector is then formed by aggregating the three vectors histograms into one vector. These vectors are accumulated in the form of binary representation and displayed as single vector. Here the similarity metric is employed to find the best combination of pixel points in the image. The color histogram is constant to rotation of the image on the projection axis, and switches in the diminished procedure are scaled or rotated. It is also insensitive to variation in image & histogram closures. The construction of the color histogram is a next iterative process, which includes scanning of the image, allocates the color values to the resolution of the histogram, and this builds the histogram using color components as an index of the image representation.

Edge and Shape Detection is the method to measure the similarity between the shapes represented by their features. Shape is a vital visualization feature and it is one of the direct features for image cognitive description. Shape content description is hard to define because appraising the similarity between the shapes is challenging. Therefore, the process completed by executing the shape and edge descriptors. Shape descriptors can be partitioned into two main classes: region based and contour-based methods. Shape descriptive features are calculated from objects shapes which include the following parameters, circular shape changes, expressive ratio, discontinuity, slant irregularity, distance irregularity, complexness, powerful correct angleness, accurateness and directedness feature of the image pixel.

Spectral hashing is otherwise known as apparitional hashing technique which generating dense binary representative codes. It is very complex to exploit the internal feature to produce the visualized representation. But it assures the simplest access mechanism. Compare to other hashing technique, spectral hashing generalizes the usage of Euclidean distance to measure the distance of two samples. This measurement process executed based on the Gaussian function which is used to form the Laplacian graph representation. But, the Euclidean distance may not precisely speculate the integral distribution of the images. In addition, when changing the distance into similarity value, the radius entity is sensitive and accurate. During this process it is often to tune its optimal value. An individual layer of binary features may not the best way to acquire the structure in the count data. It can be described by effective way to acquire the additional layers information in the form of binary features. During the execution of the learning process the image pixel information are marked in the form of index representation which provides the easiest way to access a number of features without deriving other elements.

V. SEMANTIC HASHING

Semantic hashing is as effective technique in generating compact binary codes, there is a problem that receives little attention and few efforts have been paid to exploit it. In SH, as well as other hashing methods, the Euclidean distance is usually used to measure the distance between two samples, and then the Euclidean distance is converted to similarity via a Gaussian function to construct the graph Laplacian. However, the Euclidean distance may not accurately reflect the inherent distribution of the images. In addition, when converting the distance to similarity, the radius parameter is sensitive and it is often hard to tune it to its optimal value. A single layer of binary features may not the best way to capture the structure in the count data. It can be described by efficient way to learn additional layers of binary features. After learning the first layer of hidden features, an undirected model that defines $p(v,h)$. It is a complicated, non-factorial prior on h that is defined implicitly by the weights. This peculiar decomposition into $p(h)$ and $p(v|h)$ suggests a recursive algorithm: keep the learned $p(v|h)$ but replace $p(h)$ by a better prior over h, i.e. a prior that is closer to the average, over all the data vectors, of the conditional posterior over h

It can sample from this average conditional posterior by simply applying $p(h|v)$ to the training data. The sampled h vectors are then the "data" that is used for training a higher-level RBM that learns the next layer of features. It could be initialize the higher-level RBM model by using the same parameters as the lower-level RBM but with the roles of the hidden and visible units reversed. This ensures that $p(v)$ for the higher-level RBM starts out being exactly the same as $p(h)$ for the lower-level one. Provided the number of features per layer does not decrease, show that each extra layer increases a variational lower bound on the log probability of the data.

The directed connections from the first hidden layer to the visible units in the final, composite graphical model are a consequence of the fact that we keep the $p(v|h)$ but throw away the $p(h)$ defined by the first level RBM. In the final composite model, the only undirected connections are between the top two layers, because we do not throw away the $p(h)$ for the highest-level RBM.

The first layer of hidden features is learned using a constrained Poisson RBM in which the visible units represent word counts and the hidden units are binary. All the higher-level RBM's use binary units for both their hidden and their visible layers. Each layer is updated by update rules. This greedy, layer-by-layer training can be repeated several times to learn a deep, hierarchical model in which each layer of features captures strong high-order correlations between the activities of features in the layer below. To suppress noise in the learning signal, we use the real-valued activation probabilities for the visible units of all the higher-level RBM's, but to prevent hidden units from transmitting more than one bit of information from the data to its reconstruction, the pretraining always uses stochastic binary values for the hidden units.

The variational bound does not apply if the layers get smaller, as they do in an auto encoder, but, as we shall see, the pretraining algorithm still works very well as a way to initialize a subsequent stage of fine-tuning. The pretraining finds a point that lies in a good region of parameter space and the myopic fine-tuning then performs a local gradient search that finds a nearby point that is considerably better.

Recursive greedy learning of the deep generative model:
− Learn the parameters h1 = (W1,k1,b1) of the Constrained Poisson Model.
− Freeze the parameters of the Constrained Poisson Model and use the activation probabilities of the binary features, when they are being driven by training data, as the data for training the next layer of binary features.

– Freeze the parameters h2 that define the 2nd layer of features and use the activation probabilities of those features as data for training the 3rd layer of binary features.

– Proceed recursively for as many layers as desired.

After pretraining, the individual RBM's at each level are "unrolled" to create a deep autoencoder. If the stochastic activities of the binary features are replaced by deterministic, real-valued probabilities, we can then backpropagate through the entire network to fine-tune the weights for optimal reconstruction of the count data. For the fine tuning, we divide the count vector by the number of words so that it represents a probability distribution across words. Then we use the cross-entropy error function with a "softmax" at the output layer. The fine-tuning makes the codes in the central layer of the autoencoder work much better for information retrieval.

During the fine-tuning, we want backpropagation to find codes that are good at reconstructing the count data but are as close to binary as possible. To make the codes binary, we add Gaussian noise to the bottom–up input received by each code unit.

Assuming that the decoder network is insensitive to very small differences in the output of a code unit, the best way to communicate information in the presence of added noise is to make the bottom–up input received by a code unit be large and negative for some training cases and large and positive for others.

To prevent the added Gaussian noise from messing up the conjugate gradient fine-tuning, we used "deterministic noise" with mean zero and variance 16, chosen by cross-validation. For each training case, the sampled noise values are fixed in advance and do not change during training. With a limited number of training cases, the optimization could tailor the parameters to the fixed noise values, but this is not possible when the total number of sampled noise values is much larger than the number of parameters.

To speed-up the pretraining, we subdivided both datasets into small mini-batches, each containing 100 cases,2 and updated the weights after each mini-batch. For both datasets each layer was greedily pretrained for 50 passes (epochs) through the entire training dataset. The weights were updated using a learning rate of 0.1, momentum of 0.9, and a weight decay of 0.0002 _ weight _ learning rate. The weights were initialized with small random values sampled from a zero-mean normal distribution with variance 0.01.

For fine-tuning we used the method of conjugate gradients3 on larger mini-batches of 1000 data vectors, with three line searches performed for each mini-batch in each epoch. To determine an adequate number of epochs and to avoid overfitting, we fine-tuned on a fraction of the training data and tested performance on the remaining validation data. We then repeated fine-tuning on the entire training dataset for 50 epochs. Slight overfitting was observed on the 20-newsgroups corpus but not on the Reuters corpus. After fine-tuning, the codes were thresholded to produce binary code vectors. The asymmetry between 0 and 1 in the energy function of an RBM causes the unthresholded codes to have many more values near 0 than near 1, so we used a threshold of 0.1.

VI. CONCLUSION

In this work, the imporved feature extaction process is developed to perform the classification process. The CAD system based image analysis procedure is developed with the various set of features such as edge, shape, moment, corrologram, specteal hashing and semantic hashinig. This process is executed after completing the region segmentation in the image process stage. Semantic hashing with multiple instance learning leads better outcome in the classification of the image in terms of indexed precision with respect to image pixels and image bits.

VII. REFERENCES

1. Abhishek B. Mankar et al., "Data Mining - An Evolutionary View of Agriculture," *International Journal of Application or Innovation in Engineering & Management,* Volume 3, Issue 3, March 2014.

2. Boureau Y.L, Bach F, LeCun Y & Ponce J, "Learning mid-level features for recognition," *Conference on Computer Vision and Pattern Recognition*, pp. 2559_2566, 2010.

3. Chen Y, Su W, Li J & Sun Z, "Hierarchical object oriented classification using very high resolution imagery and lidar data over urban areas," *Advances in Space Research* Vol. 43, no. 7, pp. 1101_1110, 2009.

4. Erdil, E., Ghani, M. U., Rada, L., Argunsah, A. O., Unay, D., Tasdizen, T., & Cetin, M. "Nonparametric joint shape and feature priors for image segmentation," *IEEE Transactions on Image Processing*, Vol. 26, no. 11, pp.5312_5323, Nov. 2017

5. Faria F, Dos Santos J.A, Torres S Rocha A, "Automatic classifier fusion for produce recognition," *In SIBGRAPI 2012*, Ouro Preto MG, Brazil, August 2012.

6. Faria F, Dos Santos J.A, Torres S Rocha A. "Automatic classifier fusion for produce recognition." *In Graphics, Patterns and Images (SIBGRAPI), 2012 25th SIBGRAPI Conference on*, pp. 252_259. IEEE, 2012.

7. Gonzalez R.C Woods R.E, "Digital Image Processing," *Addison Wesley Longman Publishing Co., Inc., Boston, MA, USA*, 1992.

8. Guigues L, Cocquerez J, Le Men H, "Scale-sets image analysis" *International Journal of Computer Vision,* Issue. 68, pp. 289_317, 2006.

9. Gupta, G. "Algorithm for image processing using improved median filter and comparison of mean, median and improved median filter," *International Journal of Soft Computing and Engineering (IJSCE),* Vol. 1, no. 5, pp. 304_311. 2011

10. Hill, G J et al "Open and reconfigurable hypermedia systems: a filter-based model," *Hypermedia* Vol. 5, no. 2, pp. 103_118, 1993.

11. Jie Zhang, Rujing Wang, Chengjun Xie, Rui Li, "Crop Pests Image Recognition Based on Multi-features Fusion," *Journal of Computational Information Systems,* Vol. 10, no. 12, pp. 5121_5129, 2014.

12. Kumar, S., Kumar, P., Gupta, M., & Nagawat, A. K. "Performance comparison of median and Wiener filter in image de-noising," *International Journal of Computer Applications,* Vol. 12, (0975_8887). 2010.

13. Niu, S., Chen, Q., de Sisternes, L., Ji, Z., Zhou, Z., & Rubin, D. L. "Robust noise region-based active contour model via local similarity factor for image segmentation," *Pattern Recognition*, Vol. 61, pp. 104_119, 2017.

14. Patidar, P., Gupta, M., Srivastava, S., & Nagawat, A. K. "Image de-noising by various filters for different noise," *International journal of computer applications,* Vol. 9, no. 4, 2010.

15. Mesadi, Fitsum, Mujdat Cetin, and Tolga Tasdizen. "Disjunctive Normal Parametric Level Set With Application to Image Segmentation," *IEEE Transactions on Image Processing* Vol. 26, no. 6, pp. 2618_2631, 2017.