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Event Curation and Classification Technique based on Object Detection

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ABSTRACT : In the present era of image classification keypoint selection and keypoint descriptors role is very crucial and in this paper we have presented a new "key point descriptor algorithm" using "Bag of Visual Words (BoW)" method to classify the images which detects keypoints using COSEFIRE filters by extracting the keypoint regions or visual patches. A visual descriptor has to describe the keypoints detected in a testing image in a robust manner and can easily accommodate the changes based on image conditions such as blur image, rotated image, compressed image, and light conditions and based on the results attained we refer COSEFIRE 85 filter to be the most appropriate as it provides acceptable results over our personal image data set.

KEYWORDS: Bag of Visual Words, COSEFIRE, keypoint, image descriptor, classification.

I. INTRODUCTION

The image classification is the process of keeping two or more images with similar components or keypoints into a group or category by describing the vital features of a image with training set is identified and associated with labels in training set as shown in figure 1 denotes the images in test set which has to be classified based on existing data set using the proposed methodology.

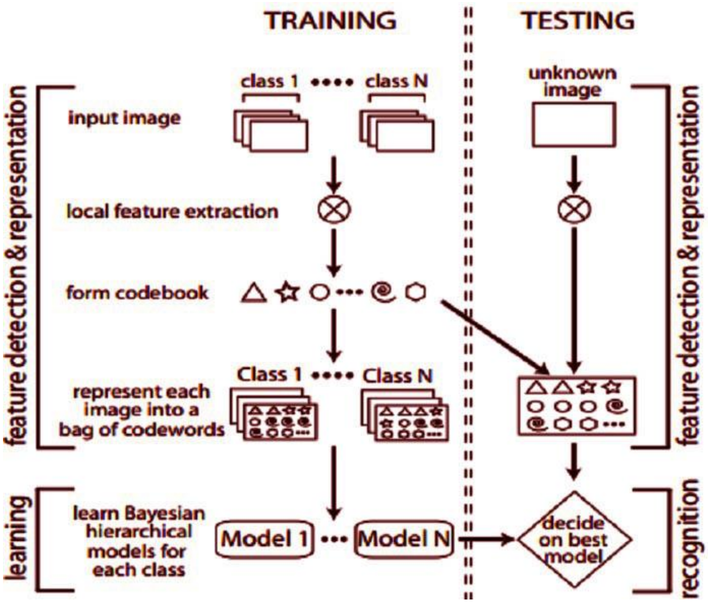


Figure 1. Bag of Visual Words (BoW) implementation [1].

The process of identifying and classifying an image or group of images based on some recognition pattern is called as the supervised learning based on which a model is constructed that relies on key points of images using which images are classified in training phase and used for predicting the image categorization in a hidden dataset [37]. In the present era of image classification and deep learning there exists many applications and gradually getting added to the list which performs image classification by using key point detection techniques includes: "face recognition, traffic lights recognition for driver less cars, crime scene categorization for robot, medical imagery classification" [2].

The depiction of Keypoint considered being one of the basic steps in computer vision because it helps in representing a specific image or group of images irrelevant of scale or transformation or position as the process uses the image descriptor which describes the image content based on the image conditions such as "different lighting conditions, angle of image rotation" are considered to be very critical in obtaining the final outcome based on the key points or interesting points based on image condition and are further converted to vector of real numbers. And when a descriptor fails to perform its task then the key point of that image will be miss mapped to a different type of image category [35]. The proposed approach is based on the descriptor using the "COSFIRE (Combination of Shifted Filter Responses) filter" [5] which is used in applications such as retinal detection [6] vascular bifurcations [7] handwritten recognition [8] traffic signs [9] computer forensics [10] though the outputs generated by these filters are tuples that are different in terms of cardinality that leads to handle fixed size output which is overcome by COSFIRE whose descriptor generates the attained output into fixed size vector by retaining the tiniest possible information [36].

Conventionally single label classification is concerned to be associated with a single label from a group of displaced labels L is denoted as $|L| > 1$, similarly when the condition (if $|L|== 2$) is met then the learning problem is considered to be a binary classification problem precisely used for web data and when the condition (if $|L| > 2$) is attained then it is considered to be a multi class classification problem. The "Bag of Visual Words (BoW)" [1] is a image classification model which comprises of attribute vectors that generate keypoint descriptors over a categorized set for a given number of clusters based on the vector quantization algorithm like K-Means [2] using which a code book is constructed to represent visual features that are extracted from a training set for every image or image set by generating a histogram of code words. In this process the keypoint detector and descriptor are applied over each training image in a iterative fashion for comparing every probable keypoint with every bin in codebook that is related to a quantized keypoint, which is known as code words along with the calculation of bin count which is the code word match count with keyponts in an image. By using this process histograms generated using the training images are used to perform the classification model using graph theory.

II. RELATED WORK:

Many researchers are doing tremendous work in this area and some of the remarkable researches done in this area are: All the keypoints are salient image patches [2] that comprises of loaded local information as the major work of a keypoint detector is to perform identification of various image patches based on the detector which identifies the corners by scaling the invariant or interesting points which are of distinct scale and represents similar keypoints [3] and there exists three keypoint detection techniques: "Difference-of-Gaussians" [4], "Hessian Laplace" [5] and "MSER" [6] after selecting the keypoints characteristics of an image are to be extracted with respect to neighborhoods [7] by scaling against image transformations and autonomous keypoint position [8] such as SIFT [9] and SURF [10] descriptors. The "Bag of visual words (BoW)" [11] is emerged from the area of text classification which is replaced with image objects that is instead of text words we use visual words [12] and the main advantage of doing so is to attain minimal computational power along with higher accuracy of classification [13] in this process the primary step in performing classification in deep learning is to detect and extracting features from the training and testing datasets [14]. Many researchers have proposed distinct keypoint detectors such as "Harrisdetector" [14], "Fast Hessian detector" [15], "Hessian Laplace detector" [16] and the "MSER detector" [17] as the "Fast Hessian detector" [15] compares the visual words using "Gaussians (DoG) detector" [18] similarly "Harris Laplace detector" [16] compresses and the "MSER detector" [17] attained better results with maximum repeatability rates over images over positive transformations [18].

The keypoint detection and description phase [19] comprises of steps where each of the keypoint region is identified and clearly described by initializing a fixed length vector for storing the information provided by visual descriptors with higher accuracy rates [20] such as "SURF descriptor" [21] "SIFT descriptor" [22] "GLOH descriptor" [23] and "BRISK descriptor" [24] which uses the sampling pattern with concentric circles where each key point is smoothed based on distance using "Gaussian smoothing" [25] and classified into short or long distance sets to identify orientation of keypoint [26].

III. THE MULTILABEL CLASSIFICATION

When we consider the predominant classification which prevails various concerns related to set of training examples denoted by h_{xi} where deliberate primary goal is to attain the "approximate function f(x)" that comprises of capability to take several values from class labels set and the problem definition is: consider X to be the group of distinct training examples and Y represents the group that comprises of 1 to k values that denote class labels where (Xi, Yi) which are indicated in:

$$X_i \in X \text{ and } Y_i \in 2^{|Y|} \tag{1}$$

Where our main target is to implement the "approximate function f(x)" which comprises of $2^{|y|}$ unique values with least error rate in multi label aspect due to the variation in definitions as the multi label approach will place the instances in a predefined order based on the learning algorithm with the function:

$$f: X \times Y \rightarrow R \tag{2}$$

In order to rank the labels the process is defined as $rank_f(x, l)$ for the label l and instance x for a given f rank will be mapped to the set from 1 to k where:

$$\text{When } (f(x, l_1) \leq f(x,l_2)) \text{ then the attained } rank_f(x,l_1) \leq rank_f(x,l_2) \tag{3}$$

IV. COSFIRE FILTER CONSTRUCTION

The construction of COSFIRE filter is a simple process which involves in considering a testing image which is used as a prototype and then points of interest is selected and which are further searched in the training data set for performing classification using "symmetric Gabor filters" [12] in which the images are blurred at the scale of λ with orientation ϴ and given as input to the filter with a tolerance threshold value to detect edges and lines where the gabor filter is denoted as:

$$Gabor_{filter}=|g_{\lambda\Theta}(x, y)|_{t1} \tag{4}$$

$$Subscription_f=\sum_{n_f}^{i=1} \lambda_i, \Theta_i, p_i, Ꝍ_i \tag{5}$$

The $subscription_f$ denotes the prototype pattern with tuples $with\ scaling\ factor\ \lambda_i$, with orentation Θ_i , with polar coordinates $p_i, Ꝍ_i$ based on the prototype complexity. For basic patterns the COSFIRE filter attains few tuple sets where as for a complex shape may attain higher cardinality which produce hurdles for novel COSFIRE descriptor construction as the keypoints needs to be created from distinct tuple sets with distinct descriptor sizes which results into vectors of constant size to generate histogram for all the four parameters in a COSFIRE filter with equal size vector descriptors to classify and generate BoW.

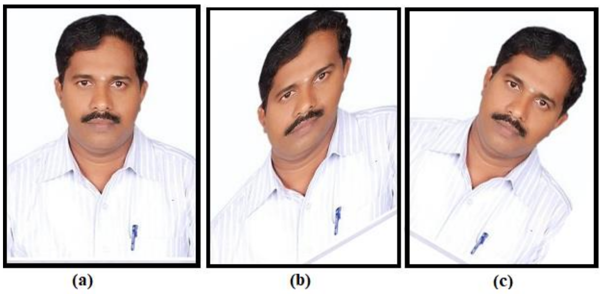


Figure 2. images example that are in graffiti viewpoint (a) denotes the original image (b) denotes the viewpoint transformation image and (c) denotes the 30degrees rotated image of the original image..

Every possible descriptor must be unique and robust from image to image based on the image conditions such as: "blurring, lightening condition, zoom factor, image compressions, and resolution" [3] are analyzed based on performance of attained COSFIRE descriptors for different environment [4] by considering a data set with upto 30degrees rotation and classifying the testing image irrespective of above mentioned conditions as shown in figure 2. The primary step in this method is to assess various visual descriptors comprises of identifying keypoints for all images in a training data set as there are many popular keypoint detectors and we consider "Maximally Stable Extremal Regions (MSER)" [13] which is based on identifying regions that lies in the area of threshold that covers extreme regions are considered to be stable with local minimum value to attain the relative square growth based on superior properties over other detectors in a image dataset. And the outliers that are identified in keypoints by descriptors are called as overlap error is the ratio attained by keypoint union and intersection is defined as:

$$OverlapError=1-{X \cap H^kYH}/{X \cup H^kYH} \tag{6}$$

Where X denotes key point in testing image, Y denotes transformed keypoints and H denotes the homographic converted image and the acceptable OverlapError must not exceed 0.5, after attaining the matching regions between testing image and training images the count of keypoint matches are calculated based on which the descriptor performance is evaluated and the duplicate keypoints score is denoted as repeatability score and this whole process is performed by MSER [16]. The $Total_{match}$ denotes correctly matched keypoints or regions is defined in equation 7 and $Total_{precision}$ denotes the total number of false matches for a keypoint or region is defined in equation 8.

$$Total_{match} = \frac{\sum_{n}^{i=1} correct_{match\,(i)}}{\sum_{n}^{j=1} communications_{\,(j)}} \quad (7)$$

$$Total_{precision} = 1 + \frac{\sum_{n}^{i=1} false_{match\,(i)}}{\sum_{n}^{j=1} correct_{match\,(j)} + false_{match\,(j)}} \quad (8)$$

Total precision is used to visualize the performance of a descriptor using a graph, if Total precision is higher than that of descriptor it is more robust and if not then the descriptor has to be updated based on the situation or need as the COSFIRE configures will be evaluated using this procedure and the best fit optimal value is selected as a part of the novel COSFIRE descriptor.

Figure 3. identification of features using COSFIRE detector [2] where yellow circle indicates the keypoint position detection with the centroid line and the green boxes denotes histograms per bin using COSFIRE descriptor

The Gussian scale space is scaled based on equation 9 where s denotes the number of scales per octave, λ is denoted for scale of the image and ϴ denotes number of octaves per image when the image is compared and classified based on the multi label to local extreme, though there exist some outlier keypoints which are close to edges based on the threshold value are to be ignored for boosting the efficiency of a descriptor. Then the COSFIRE filter is created by considering the COSFIRE keypoints for each keypoint location of an image and the image bonding is evaluated based on threshold value and results are generated as shown in figure 3.

The vectors that are generated based on descriptor are classified and clustered based on the K-Means [26] in the form of visual words, where K determines the number of centers based on which the centers are calculated and assigned which is the most typical part because different centroids will generate different results, so one solution is to attribute the nearest matching image as a keypoint vector until all the images are compared in the training set. By implementing this we will get k number of visual words from the generated vocabulary that are further denoted into fixed size vectors with$\sum_{n}^{i=1} descriptors$, based on which the distance between each visual word is calculated using "Euclidean distance measure" [27] and then the histogram is constructed with the values of visual bins that are incremented or decremented based on the nearest keypoint centroid value using "K Nearest Neighbor (KNN) classification".

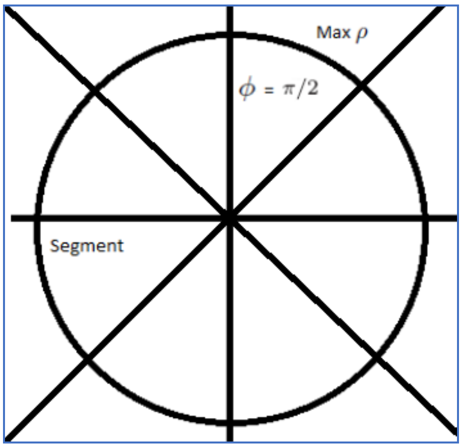


Figure 4. grid consisting of 8 sectors and 1 circle resulting into 8 segments based on their locations

There exist many COSFIRE filters with distinct cardinality hence we propose to develop a histogram for each keypoint to produce a fixed size COSFIRE descriptor where every histogram comprises of consists of the values determined by λ_i parameters with i bins which are $\{\sqrt[2]{2}, 4, \sqrt[4]{2}, 8, \sqrt[8]{2}\}$ and the polar coordinate $, \Theta_i$ comprises of i bins which are {0, 0.4, 0.8, 1.2, 1.6, 2, 2.4, 2.7, 3.1, 3.5, 3.9, 4.3, 4.7, 5.1, 5.5, 5.9} based on these values a polar grid is formulated using max and min values of circle which is further sub divided into many circles based on the required sectors. As shown figure 4 the COSFIRE descriptor comprises of 8 segments and 1 circle by which 8 polar grids can be further generated.

All the areas generated will be assigned with a unique ID then verification is done to determine whether any loops have been formed in areas and then verification is done to determine whether (p_i, Θ_i) fits in the desired criteria which is the sector circular boundary then each tuple is plotted in the polar grid based on p_i, Θ_i values as they also provide the location. Based on these properties a histogram is generated using bins and are further normalized by which the values are normalized because keypoints detected for each feature is distinct for each future or different histograms are concatenated to form a new histogram which is the COSFIRE descriptive information. Initially all the descriptor are constructed using $hist_\Theta + hist_{seg} + hist_\lambda$ using these values distinct parameter combinations are evaluated because of which the COSFIRE descriptor is of distinct sizes and based on these values circles and sectors are generated to attain the performance measure. For example if we use 12Θ values, 4 polar grids, and 5λ values the size of the descriptor becomes (12+4+5) that is 21, as it is stored in vector these values can be further modified to control the polar grid in this fashion distinct polar grids are formed and analyzed to attain the performance of COSFIRE descriptor later it is compared with any of the novel descriptors.

Several COSFIRE descriptor’s with distinct configurations have been implemented and executed and in most of them the process comprises of initially acquires MSER features data of each image which includes the parameter details such as Ellipse and Cartesian location values. One of the major issue in measuring the scale of different keypoint regions as they have different scales on which the performance of descriptor is based in measuring the photometric transformations and the solution we propose is to use affine covariant construction which has the potential to map all ellipses with the keypoint regions within a threshold radius as shown in figure 5. The keypoint feature detector [4] is used for performing classification comprises of three parameters: The first parameter is keypoint detector will consider each image scale to be full resolution by setting the octave index to -1, the second parameter is the edge threshold which performs eliminate the space of DoG scale when its value is almost negligible space by which localized freames are secured and value 60 is assidnged to data set and the third parameter is elimination of Difference of Gaussian(DoG) scale by assigning the threshold value to 5 for every dataset and this process is represented in figure 6.

Figure 5. (a) denotes the detected feature and (b) denotes that correction performed through affine covariant construction by rotation

(a) (b)

Figure 6. illustrates features extracted from the testing image with default SIFT identifier values (a) and the optimized values (b)

Algorithm: Event Curation and Classification Technique

Step 1: Start
Step 2: Approximate function f(x)
Step 2.1: Generate class labels using training samples and Y={1,….., k}
Step 2.2: $f = |X \times Y \rightarrow R|$, where $X_i \in X$, $Y_i \in 2^{|Y|}$
Step 3: Rank the labels $rank_f(x, l)$
Step 3.1: when $(f(x, l_1) \leq f(x, l_2))$ then the $rank_f(x, l_1) \leq rank_f(x, l_2)$
Step 4: Construction of COSFIRE filter
Step 4.1: Classification of images using, $Gabor_{filter} = |g_{\lambda\Theta}(x, y)|_{t1}$
Step 4.2: Generate prototype pattern, $Subsciption_f = \sum_{n_f}^{i=1} \lambda_i, \Theta_i, p_i, \Phi_i$
Step 4.3: Generation of keypoints(blurring, lightening condition, zoom factor, image compressions, and resolution)
Step 5: Conversion of Homographic Image
Step 5.1: $OverlapError = 1 - {X \cap H^k YH}/{X \cup H^k YH}$
Step 5.2: $Total_{match} = \frac{\sum_{n}^{i=1} correct_{match(i)}}{\sum_{n}^{j=1} communications_{(j)}}$
Step 5.3: Visualize the performance, $Total_{precision} = 1 + \frac{\sum_{n}^{i=1} false_{match(i)}}{\sum_{n}^{j=1} correct_{match(j)} + false_{match(j)}}$
Step 5.4: If (OverlapError >1) then goto step 2.
Step 5.5: If ($Total_{precision} < Total_{match}$) then goto step 4.
Step 5.6: $BestFit_{Optimal} = bestfit(Total_{match}, Total_{precision})$
Step 5.7: Generate COSFIRE keypoints
Step 5.8 : $BagofVisualWords_{bins} = euclidean\_measure(\sum_{n}^{i=1} descriptors)$

Step 6: Stop

V. EXPERIMENTAL RESULTS

This COSFIRE descriptor that we have considered is comprises of 336 dimensionality which is really a higher one as each dimension gives us much more information regarding the location of tuples in the filter. Let us consider 4 types of images which are converted to blur, change in light, rotating a image, taking a JPEG compressed image as shown in figure 7.

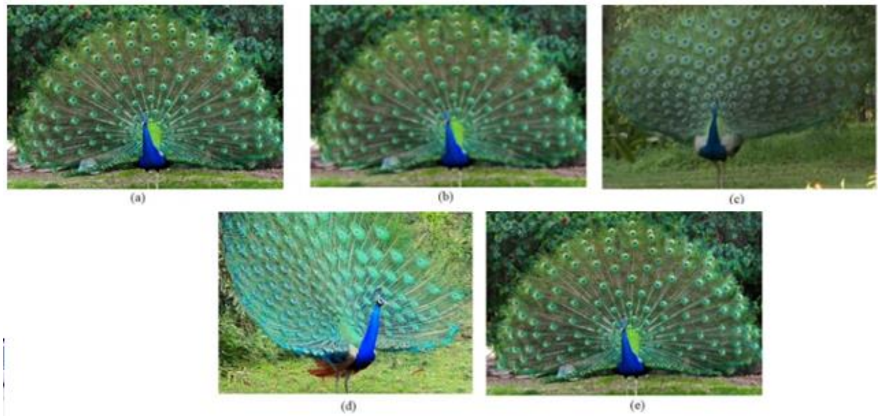
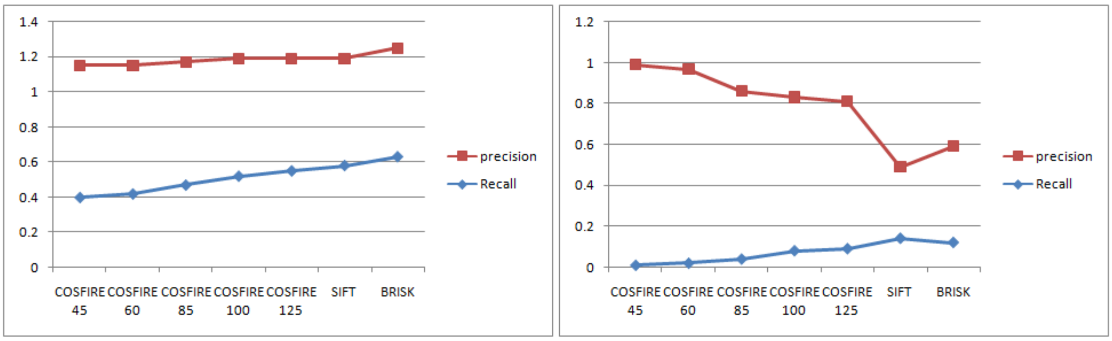


Figure 7. sample images considered in our own dataset with varying image conditions (a) testing image (b) converted to blur (c) change in light (d) rotating a image view (e) compressed image

The structured scene is the image which comprises of objects with some sort of texture repetition where the testing image will not match exactly and the performance has to be measured by counting the correct matches number probably when a descriptor attains 400 nearest neighbor matches by considering corresponding regions of the images and based on the analysis we can say that blur images comprises of more number of edges as shown in figure 8.



(a) (b)

Figure 8. plotting of blur categories with Recall vs 1-Precision plots using COSFIRE descriptors with 400 matches structured images (a) and textured images(b)

Based on the above figures related to results attained for 400 matches performed on image to classify using Bag of Visual words (BoW) we can say that the performance attained by COSEFIRE 85 is closely associated with SIFT when we consider the averages generated for these values hence it is clear that we need to combine λ and Θ values as per equation 4 which will give us better performance of the descriptor of a visual word as λ denotes edges.

VI. CONCLUSION

In this paper we have presented an algorithm for Bag of Visual Words (BoW) method to classify the images based on events and by detecting the keypoints using COSEFIRE filters to extract the keypoint regions in different types of images with distinct conditions and based on the results attained we can say that COSEFIRE 85 is most appropriate to provide better results over our personal image data set with generation of histogram using λ and Θ values to attain the cross validation accuracy and though some of the descriptors are week in our experimental study which has to be overcome in future study and along with this we need to thoroughly analyze the Cartesian areas related to keypoints in a polar grid is to be performed.

REFERENCES

[1] L. Fei-Fei and P. Perona, “A bayesian hierarchical model for learning natural scene categories,” in Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on, vol. 2, pp. 524–531, IEEE, 2005

[2] V. B. Subburaman, A. Descamps and C. Carincotte, "Counting people in the crowd using a generic head detector," Advanced Video and Signal-Based Surveillance, IEEE Ninth International Conference, 2012, pp. 470-475 .

[3] S. Thakur, S. Paul , A. Mondal and S. Das "Face detection using skin tone segmentation." IEEE World Congress on Information and Communication Technologies, 2011, pp. 53-60.

[4] Gonzalez, et . al . Digital Image Processing , 3rd edn. , Prentice Hall, Upper Saddle River, -2008.

[5] V.Ara. H Monson and Nefian,"Hidden Markov models for facerecognition." choice 1, 1998.

[6] M.ouret, Marc, C. Solnon, and .Wolf. "Classification of images based onHidden Markov Models." Content-Based Multimedia Indexing, 2009. CBMI'09. Seventh International Workshop on. IEEE, 2009.

[7] Ali Shaik, M."Time series forecasting using vector quantization", International Journal of Advanced Science and Technology, 2020,volume: 29,number: 4, pp: 169-175.

[8] Wang, Lipo “Support vector machines: theory and applications”. Vol. 177. Springer Science & Business Media, 2005.

[9] Melgani, Farid, and L. Bruzzone. "Classification of hyperspectral remote sensing images with support vector machines." Geoscience and Remote Sensing, IEEE Transactions on 42.8, 2004, pp. 1778-1790..

[10] Shen, Linlin, Li Bai, and Z. Ji. "A SVM face recognition method based on optimized Gabor features." Advances in Visual Information Systems. Springer Berlin Heidelberg, 2007, pp. 165-174.

[11] Ali Shaik, M."A survey on text classification methods through machine learning methods", International Journal of Control and Automation", 2019,volume: 12,number: 6, pp: 390-396.

[12] Bernd Heisele, P. Ho and T. Poggio, "Face recognition with support vector machines: Global versus component-based approach", Computer Vision 2001. ICCV 2001. Proceedings. Eighth IEEE International Conference on, vol. 2, 2001.

[13] Joachims and Thorsten, "Text categorization with support vector machines: Learning with many relevant features" in Kan Xie Support Vector Machine (Concept and Matlab Build) ECE 480 Team4, Springer Berlin Heidelberg, 1998.

[14] Iancu et al., "A Review of Hidden Markov Models in Face Recognition", 2011.

[15] Supardi et al., "Development of Artificial Neural Network Architecture for Face Recognition in Real Time", International Journal of Machine Learning and Computing, vol. 4, no. 1, 2014.

[16] Marius Diedrick, Sumita Pennathur and Klint Rose, "Face detection using color thresholding and eigenimage template matching", Digital Image Processing project, 2003.

[17] Ali Shaik, M. and Sampath Kumar, T. and Praveen, P. and Vijayaprakash, R., "Research on multi-agent experiment in clustering, "International Journal of Recent Technology and Engineering", 2019,volume: 8,number: 1 Special Issue 4, pp: 1126-1129.

[18] Hota et al., "Face detection by using skin color model based on one class classifier", Information Technology 2006. ICIT'06. 9th International Conference on, pp. 15-16, 2006.

[19] Singh Sanjay Kr et al., "A robust skin color based face detection algorithm", Tamkang Journal of Science and Engineering, vol. 6, no. 4, pp. 227-234, 2003.

[20] K. S. Deshpande, C. B. Tatepamulwar, H. S. Fadewar and V. P. Pawar, "Skin Color Based Face Detection", International Journal of Advanced Research in Computer Science and Software Engineering, vol. 5, no. 6, pp. 1103-1109, 2015.

[21] Ali Shaik, M."Protecting Agents from Malicious Hosts using Trusted Platform Modules (TPM), "Proceedings of the International Conference on Inventive Communication and Computational Technologies, ICICCT 2018",2018, pp: 559-564.

[22] i Deng. 2014. A tutorial survey of architectures, algorithms, and applications for deep learning.APSIPA Transactions on Signal and Information Processing3 (2014), 1–29.

[23] Yilin Yan, Min Chen, Saad Sadiq, and Mei-Ling Shyu. 2017. Efficient imbalanced multimedia concept retrieval by deep learning on spark clusters. International Journal of Multimedia Data Engineering and Management8, 1 (2017), 1–20.

[24] Yilin Yan, Min Chen, Mei-Ling Shyu, and Shu-Ching Chen. 2015. Deep learning for imbalanced multimedia data classification. In The IEEE International Symposium on Multimedia. IEEE, 483–488.

[25] Warren S. McCulloch and Walter Pitts. 1943. A logical calculus of the ideas immanent in nervous activity.Bulletin of Mathematical Biophysics5, 4 (1943), 115–133.

[26] Jürgen Schmidhuber. 2015. Deep learning in neural networks: An overview.Neural Networks61 (2015), 85–117.

[27] Yann LeCun and Yoshua Bengio. 1995. Convolutional networks for images, speech, and time series. Handbook of Brain Theory and Neural Networks3361, 10 (1995), 255–257.

[28] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton. 2012. ImageNet classification with deep convolutional neural networks. InAdvances in Neural Information Processing Systems 25, F.Pereira, C.J.C.Burges, L.Bottou, and K. Q. Weinberger (Eds.). Curran Associates, 1097–1105.

[29] Ruslan Salakhutdinov and Geoffrey Hinton. 2009. Deep Boltzmann machines. InArtificial Intelligence and Statistics. PMLR, 448–455.

[30] Ruslan Salakhutdinov and Geoffrey Hinton. 2012. An efficient learning procedure for deep Boltzmann machines. Neural Computation24, 8 (2012), 1967–2006.

[31] Kyunghyun Cho, Bart van Merrienboer, Çaglar Gülçehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. 2014. Learning phrase representations using RNN encoder-decoder for statistical machine translation. InThe Conference on Empirical Methods in Natural Language Processing. 1724–1734.

[32] Xiangang Li and Xihong Wu. 2015. Constructing long short-term memory based deep recurrent neural networks for large vocabulary speech recognition. InIEEE International Conference on Acoustics, Speech and Signal Processing. IEEE, 4520–4524.

[33] Mohammed Ali Shaik and Dhanraj Verma, (2020), Enhanced ANN training model to smooth and time series forecast, 2020 IOP Conf. Ser.: Mater. Sci. Eng. 981 022038 https://doi.org/10.1088/1757-899X/981/2/022038

[34] Mohammed Ali Shaik, Dhanraj Verma, P Praveen, K Ranganath and Bonthala Prabhanjan Yadav, (2020), RNN based prediction of spatiotemporal data mining, 2020 IOP Conf. Ser.: Mater. Sci. Eng. 981 022027 https://doi.org/10.1088/1757-899X/981/2/022027

[35] Mohammed Ali Shaik and Dhanraj Verma, (2020), Deep learning time series to forecast COVID-19 active cases in INDIA: a comparative study, 2020 IOP Conf. Ser.: Mater. Sci. Eng. 981 022041 https://doi.org/10.1088/1757-899X/981/2/022041Christoph Goller and Andreas Kuchler. 1996. Learning task-dependent distributed representations by backpropagation through structure. InIEEE International Conference on Neural Networks, Vol. 1. IEEE, 347–352.

[36] Richard Socher, Cliff C. Lin, Chris Manning, and Andrew Y. Ng. 2011. Parsing natural scenes and natural language with recursive neural networks. InInternational Conference on Machine Learning. Omnipress, 129–136.

[37] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. Generative adversarial nets. InAdvances in Neural Information Processing Systems. Curran Associates, 2672–2680.