International Journal of
Intelligent Systems and Applications in Engineering

ISSN:2147-6799 www.ijisae.org Original Research Paper

Human Action Recognition on Real Time and Offline Data

Geetanjali Kale[1], Jayashri Jawale[2], Priyanka Dhende[3], Komal Abak[4], Harshada Koshti[5]

Accepted : 20/03/2019 Published: 21/03/2019

Abstract: Abstract: Human action recognition is an important area of research in the field of computer vision due to its extensive applications like security surveillance; content based video retrieval and annotation, human computer interaction, human fall detection, video summarization, robotics, etc. The surveillance system deals with the monitoring and analysing the human behaviour and activities. The main aim of the smart surveillance system is to recognize anomalous behaviour in given scene and provide real time intimation to relevant person. We have designed and tested Smart Surveillance System for College Corridor Scene (3S2CS). The system recognises the anomalous behaviour and an intimation is provided in the form of Firebase Cloud Messaging (FCM) alert on the android mobile phone to the authorised user. This paper mainly discuss the methodologies used for the human action recognition. The basic step is to provide video as an input. These videos are further divided into number of frames. The videos are used for training and for each video, Scale Invariant Feature Transform (SIFT) is applied for extracting features and developing feature vectors. The actions are classified using K Nearest Neighbour (KNN) and Support Vector Machine (SVM) classifier. Two standard offline datasets considered for testing are Weizmann and UTD-MHAD. For real time scenario we have created dataset in college campus called as College Corridor dataset. It contains student activities like falling, fighting, walking, running, sitting and other general actions. If falling or fighting action is detected, the notification is sent to the authorized user who has installed ActionDetector android application and registered a device for the same. Action recognition accuracy is 92.91% using SVM and 90.83% using KNN.

Keywords: *Computer Vision, SIFT, SVM, KNN, Human Action Recognition, FCM Alert*

1. Introduction

Human Action Recognition involves many applications such as security surveillance, human machine interaction, sports, medical diagnostics and entry, exit control etc. Major steps involved in human motion analysis are capturing, object / human tracking, object and motion representation and recognition of human activities [1]. Significant amount of work is done in domain Human Action Recognition involves many applications such as security surveillance, human machine interaction, sports, medical diagnostics and entry, exit control etc. Major steps involved in human motion analysis are capturing, object / human tracking, object and motion representation and recognition of human activities [1]. Significant amount of work is done in domain however; detection of human activities remains a challenging task. Main reasons behind this are variable appearance, wide range of poses that they can adopt, in-class variance in all action categories, and large range of actions from simple gesture to complicated group behaviour. Focus of this paper is on anomalous human behaviour or interaction in college corridor. This extremely important issue needs special attention, as there can be situations like slipped on floor while running or walking, kicked, punched or pushed by someone. These situations need to be reported to security or responsible person. Proposed Smart Surveillance system considers six classes of college corridor activities and system reports the anomalous behaviour to the registered mobile device.

Section 2 discuss about the related literature, section 3 gives the architecture of 3S2CS system, related algorithms, and datasets, results are discussed in section 4 and conclusion and discussion is given in section 5.

2. Related Literature

Human activity detection is a challenging, unsolved problem and researchers are working on it from late 70's. This section discusses about related literature and advances in domain. Du Tran et. al proposed metric learning based approach for human activity recognition. Main objectives of work were (1) to reject unfamiliar activities and (2) to learn with few examples. Method has outperformed over the state of art on standard dataset and worked well on noisy Youtube dataset [3]. Subspace clustering can handle multi-dimensional data that are not possible with the typical clustering method. However, it aims in fusing a large contextual information such as emotions, health conditions [4]. As the conventional clustering process could not handle the multidimensional data, it is possible to improve the activity recognition by applying subspace clustering. It utilizes a typical method, which is a density-based clustering method that acquire clusters in axis-parallel subspaces. Data acquisition is performed by the sensors and features that are needed for recognizing the human activity are extracted and the clusters are obtained using density based clustering method [5] [6]. Many times feature extraction methods are used to describe the human actions. The features are usually synthesized into descriptors. Shape contexts and SIFT descriptors are most popular descriptors in this area [7].

[1]*Assistant Professor at PICT, Pune, India*
[2] *Student of PICT, Pune, India*
[3]*Student of PICT, Pune, India*
[4]*Student of PICT, Pune, India*
[5]*Student of PICT, Pune, India*
* *Corresponding Author Email: gvkale@pict.edu*

Generally, these descriptors encode the body looks and some context of motion. Lowe and David G categorizes human motion using hybrid of spatial-temporal and static features [8]. The system designed by Niebles et.al classifies the activities and detects abnormality using approach that is introduced for multi-class SVM classification, which checks for the states that are unreachable from the current state and avoids them [10]. The system is designed by Iqbal et. al to detect old people fall detection by extracting features using SIFT and then making comparisons using Hidden Morkov Model (HMM) [11]. The nearest neighbour (NN) classifiers, is among the simplest and most efficient classification rules and are widely used in practice KNN mainly used for statistical pattern recognition and the supervised neural network learning points of view [12]. The KNN classification algorithm is applied for handwritten digit recognition efficiently [13]. The different complexity of action. Hierarchical approaches have shown great success for the recognition of complicated actions and interactions. The techniques like bag-of-words, and HMM that have shown success in speech and text recognition are successfully applied for action recognition [14]. Three main technologies used for capturing videos are RGB camera, depth sensor and wearable device. It is found that the popularity of RGB camera in HAR research has dropped while both depth and wearable sensors are the substitutes. On the other hand, the use of Kinect sensor (depth sensor) into HAR system is promising and somewhat expensive. Some challenges involved in human activity recognition are application domain, occlusion, background and recording settings, learning paradigm usage, variations in Inter and Intra class, etc. [15]. Chaquet et. al have given comparison between the different datasets and for the sake of clarity, the main characteristics of the 28 public video datasets for human action and activity recognition described [16]. We have considered the Weizmann and UTD-MHAD standard datasets before going for the real time applications, and created College Corridor dataset in college campus. The suspicious activities are notified to the end user on smart phone application the system with real time application of College Corridor scenario.

3. Smart Surveillance System for College Corridor Scene (3S2CS)

S^3C^2S system mainly consists of three different layers that are client layer, application layer and database server layer. The client layer includes the user android application to receive notifications. Only authorised users can receive alert about anomalous action detection.

Application layer consists of main human action Recognition system.

At database server layer, there is Google server and apache tomcat local server to handle the services of human action recognition system. For College Corridor scenario, dataset is created at PICT corridor with six action classes fighting, falling, walking, running, sitting and general action class. If actions like fighting or falling are detected by the system then, the notification is sent to the user who has installed the android application and registered for the same.

The system takes video as an input, performing grayscale conversion and pre-processing steps, feature extraction is done using SIFT. These extracted features are used for action classification purpose. SVM and KNN classifiers are used for activity classification. The system results show the comparison between SVM and KNN algorithms used for dataset classification. Apache tomcat server is installed for maintaining the database of notification and registration token which is required by FCM.

Service. Apache tomcat is an open source web server that implements Java Server Pages (JSP) specifications. We are using FCM for sending notification to the registered device. FCM is a cross-platform solution provided by Google for messages and notifications for ios, web applications and android. A message can transfer a payload of up to 4KB to a client application using FCM for an instant messaging. This service is used to inform the client about suspicious action is detected we are using with the authentication of the user. Currently surveillance system and the authorised user are assumed in same wireless network at college campus. However, android application can be extended to use from anywhere using internet.

3.1. Scale Invariant Feature Transform (SIFT):

SIFT is used for feature extraction which extracts key points and compute its descriptors. SHIT features are invariant to direction, scaling, and also partly invariant to lighting variations and affine distortion. This helps to accurately recognize objects with noise and fractional occlusion. It has good recall rates, included in OpenCV library. It is -relatively efficient as compared to older algorithms. The features are extracted for the trained videos and the feature vectors are developed. Test videos are given as input to system and SIFT features are extracted. These features further given as input for action recognition system. SIFT finds out key points from images and extract the descriptor for each keypoint. 128-bit descriptor is stored for each key point.

There are mainly four steps involved in SIFT algorithm [17]

I. Find Scale Space Extrema – An internal representation of original image.
II. Keypoint Localization and Filtering – It selects significant key points removes least significant points.
III. Orientation Assignment – It removes effects of rotation and scaling.
IV. Descriptor Creation – It is done using histograms of orientations.

3.2. Action Classification Method

Action classification and prediction is important steps in human motion data analysis. Researcher for human motion classification successfully applies the different classifiers. This work uses KNN and SVM classifier applied for classification activity video in different action classes. The classifier is built from the training set associated with class labels. The training dataset is vectors in a multidimensional feature space, each with a class label.

3.2.1. K-Nearest Neighbor Classifier

As its name suggest the KNN algorithm finds the nearest matching from training dataset. The distance is calculated between the new feature vector and every vector of the training set. Euclidian distance measure is used for this purpose. Simple majority vote of the nearest neighbors of every point is computed using KNN classifier. Data class label of the most representative class is assigned to the key points extracted from query (test) video. It implements learning based on the k nearest neighbours of each query point where k is integer value given by user. The basic step used for nearest neighbour's classification is uniform weights, that is, the value assigned to a query point is computed from a simple majority vote of the nearest neighbours. Sometimes, it is better to weight the neighbours such as nearer neighbours contribute more to the fit. This can be accomplished by specifying weight values.

The 'uniform' value of weight assigns uniform weights to each neighbour.

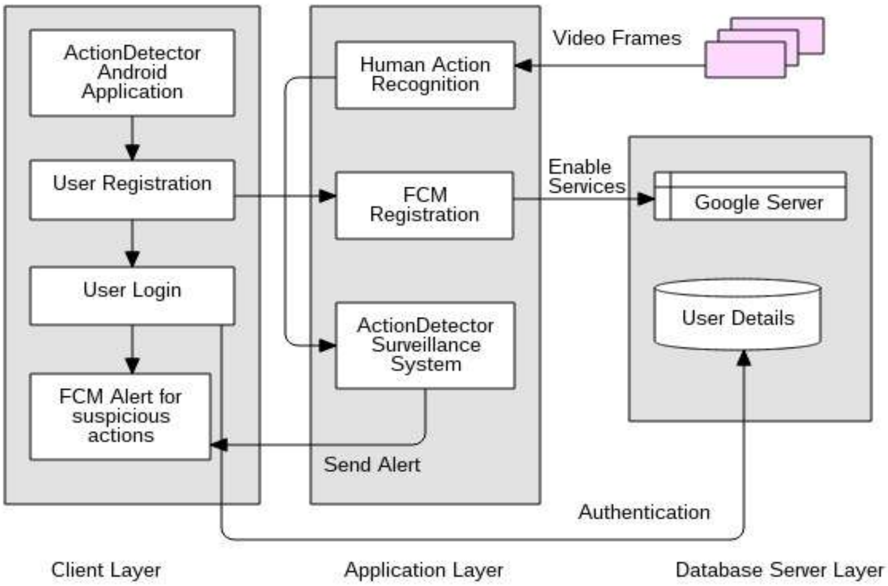

Figure 1. Architecture diagram of smart surveillance system for College Corridor Scenario (S^3C^2S)

3.2.2. SVM Classifier

SVM is a supervised learning method for classification and regression. Comparative to other classifiers it gives good results. It is effective in high dimensional spaces, though the number of dimensions are greater than the number of samples. If the training data is not linearly separable then the kernel functions are used to transform data to new space. Different kernels can be used like Linear kernel, RBF kernel, Polynomial kernel and Sigmoid Kernel. We have used linear kernel which uses one vs rest comparisons in multi classification, where fitting of one classifier per class is done. For each classifier, the class is fitted against all the other classes, N number of classes use N classifiers. Whereas, One vs One method constructs one classifier per pair of classes and during prediction, the class which received the most votes gets selected. In case of a tie that is if two classes with an equal number of votes predicted then, it selects the class with the highest aggregate classification confidence. It requires to fit $N(N–1)/2$ classifiers for N number of classes. We used the Libsvm based implementation with One vs One classification scheme using RBF kernel.

3.3. Dataset Description

We have used three datasets Weizmann dataset, UTD Multimodal Human Action Dataset for RGB videos and our own created dataset at PICT College Corridor. We have used all the three datasets considering single view. These datasets are summarized in table 1. These three datasets represent the multiple actors, actions and number of sequences. Weizmann dataset consists just one instance of activity per actor and UTD-MHAD has 4 instances of each activity for every different actor. Therefore, there are extensive repetitions in UTD-MHAD. In College Corridor dataset there are 10 repetitions of each actor for every action.

3.3.1. Weizmann Dataset

The Weizmann action dataset consists of 10 different actions performed by 9 different actors. There are total 90 different videos captures using single camera in static background. "The Weizmann

(a) Weizmann

(b)) UTD-MHAD

(c) College Corridor Scenario

Figure 2. Sample frames from (a) (b, (c) dataset

Institute of Science (Faculty of Mathematics and Computer Science, Israel) records it in 2005. Database of 90 low-resolution (180 x 144, deinterlaced 50 fps) video sequences collected on a nine different persons. Ten different actions are walking, running, jumping, siding, skipping, bending, one hand waving, two hand waving, jumping in place and jumping jack. It contains both periodic and non-periodic actions.

Table 1. Summarization of Activity Datasets

Dataset	Actors	Repetition	Actions	Sequences
Weizmann	9	1	10	90
UTD-MHAD	8	4	27	192
College Corridor Dataset	4	10	6	240

3.3.2. UTD-MHAD Dataset

This dataset was collected using a Microsoft Kinect sensor and a wearable inertial sensor in an indoor environment. The dataset contains 27 actions as jogging, squat, boxing, clapping, walking, pushing, swipe left, swipe right, sit to stand, jogging in place, right hand waving, etc. performed by 8 subjects. Each subject has repeated every action 4 times. The dataset is published by department of electrical engineering, university of Texas at Dallas for research purpose in 2015. We have considered 6 different actions jogging, boxing, clapping, squat, walking, pushing by 4 subjects with 2 repetitions for training purpose. We have tested for this 6 different activities by 8 subjects with 4 repetitions and the results are analysed.**College Corridor Scenario Dataset**

College Corridor Scenario dataset has six classes of activities to be detected that are falling, fighting, walking, running, sitting and other general actions. In fighting activity, we have included actions like boxing, punching, kicking, slapping, pushing, etc. whereas, in falling activity, the actions included are slipping and a sudden fall. We have collected data from 4 to 5 actors with 2 to 3 repetitions each. We have not trained all the videos which are captured but tested all the videos from dataset. Around one-half videos are trained. During training, some of the repeated videos of same activity are not considered during training.

4. Results

Weizmann, UTD-MHAD and College Corridor datasets are tested using KNN and SVM classifiers and their results are analyzed and discussed in this section.

Table 2. Results of 3S2CS system on Weizmann, UTD-MHAD and College Corridor Dataset

(a): Confusion Matrix for results using SVM on Weizmann Dataset

		Predicted Classes									
		Skip	**Bend**	**Run**	**Wave2**	**Jack**	**Side**	**Jump**	**Wave1**	**Walk**	**Jump**
Actual Classes	**Skip**	**8**	0	0	0	0	0	0	0	0	0
	Bend	0	**9**	0	0	0	0	0	0	0	0
	Run	0	0	**9**	0	0	0	0	0	0	0
	Wave2	0	0	0	**9**	0	0	0	0	0	0
	Jack	0	0	0	0	**9**	0	0	0	0	0
	Side	0	0	0	0	0	**9**	0	0	0	0
	Jump	0	0	0	0	0	0	**9**	0	0	0
	Wave1	0	0	0	0	0	0	0	**9**	0	0
	Walk	0	0	0	0	0	0	0	0	**9**	0
	Jump	0	0	0	0	0	0	0	0	0	**9**

(b). Confusion Matrix for results using KNN on Weizmann Dataset

		Predicted Classes									
		Skip	**Bend**	**Run**	**Wave2**	**Jack**	**Side**	**Jump**	**Wave1**	**Walk**	**Jump**
Actual Classes	**Skip**	**7**	0	0	0	0	0	0	0	0	0
	Bend	0	**9**	0	0	0	0	0	0	0	0
	Run	0	0	**9**	0	0	0	0	0	0	0
	Wave2	0	0	0	**9**	0	0	0	0	0	0
	Jack	0	0	0	0	**9**	0	0	0	0	0
	Side	0	0	0	0	0	**9**	0	0	0	0
	Jump	0	0	0	0	0	0	**9**	0	0	0
	Wave1	0	0	0	0	0	0	0	**9**	0	0
	Walk	0	0	0	0	0	0	0	0	**9**	0
	Jump	0	0	0	0	0	0	0	0	0	**9**

(c). Confusion Matrix for results using SVM on UTD-MHAD Dataset

		Predicted Classes					
		Boxing	**Clapping**	**Jogging**	**Pushing**	**Squat**	**Walking**
Actual Classes	**Boxing**	**30**	2	0	0	0	0
	Clapping	0	**30**	0	0	0	0
	Jogging	0	0	**31**	0	1	1
	Pushing	2	0	0	**32**	0	0
	Squat	0	0	0	0	**31**	0
	Walking	0	0	1	0	0	**31**

(d). Confusion Matrix for results using KNN on UTD-MHAD Dataset

		Predicted Classes					
		Boxing	**Clapping**	**Jogging**	**Pushing**	**Squat**	**Walking**
Actual Classes	**Boxing**	**29**	2	0	0	0	0
	Clapping	0	**30**	0	0	0	0
	Jogging	0	0	**31**	0	1	1
	Pushing	2	0	0	**32**	0	0
	Squat	0	0	0	0	**31**	0
	Walking	0	0	1	0	0	**29**

Table 2 (e) Confusion Matrix for results using SVM on College Corridor Dataset

		Predicted Classes					
		Falling	Fighting	Walking	Sitting	Running	General
Actual Classes	**Falling**	**36**	2	0	2	0	1
	Fighting	0	**35**	0	0	0	0
	Walking	0	0	**37**	0	2	0
	Sitting	0	0	0	**38**	0	0
	Running	0	0	2	0	**38**	0
	General	4	3	1	0	0	**39**

Table 2(f). Confusion Matrix for results using KNN on College Corridor Dataset

		Predicted Classes					
		Falling	Fighting	Walking	Sitting	Running	General
Actual Classes	**Falling**	**36**	0	0	3	0	1
	Fighting	0	**35**	0	0	0	1
	Walking	0	0	**36**	0	3	0
	Sitting	4	0	0	**37**	0	0
	Running	0	0	3	0	**36**	0
	General	0	5	1	0	1	38

Table 2 shows the performance of both classifiers on three mentioned datasets. All 90 sequences given in Weizmann dataset are considered to test the algorithms. 10 actions X 9 persons = 90 sequences. Recognition results by SVM and KNN classifiers are shown in table 2(a) and table 2(b). Action recognition accuracy is 98.88% using SVM and 97.78% using KNN. Even though UTD-MHAD has 27 actions, we have considered selected six actions to test 3S2CS system. Considered six actions are – boxing, clapping, jogging, pushing, squat, walking. 6 actions X (4 male + 4 female) X 4 repetitions = 192 action sequences are tested. Recognition results by SVM and KNN classifiers are shown in table 2(c) and table 2(d). Action recognition accuracy is 96.35% using SVM and 93.23% using KNN. College Corridor Scenario dataset has 6 classes X 10 actors X 4 repetitions = 240 sequences and data is tested real time. Recognition results by SVM and KNN classifiers are shown in table 2(e) and table 2(f). Action recognition accuracy is 92.91% using SVM and 90.83% using KNN. From recognition results, it is observed that SVM outperform over the KNN for all three datasets.

It has also been observed that overall recognition rate for our dataset is less as compared to other two standard datasets. Main reason behind this is involvement of more than one actor in dataset. Scenario like fighting always involve more than one person and dataset involving multiple persons is more realistic. Also, slow running is miss-classified as walking and fast walking is miss-classified as running. Classifier is confused between falling down and sitting down for few cases.

5. Conclusion

The system gives overview of human action classification using supervised learning algorithm. The paper mainly discuss computer vision algorithms SIFT, KNN and SVM. Features are extracted using SIFT as it is scale invariant algorithm and it can accurately represents object even along with noise and fractional occlusion. Then the extracted features are given to the SVM and KNN algorithms for action classification. Training and testing is performed on three different datasets. The results are collected for these two classifiers on three datasets. The SVM with RBF (radial basis function) kernel gives better results as compared to the KNN classification algorithm. We have obtained good prediction accuracy using SVM algorithm. Actions like sitting down and falling down are very similar and requires special attention while devising the classification algorithms.

The surveillance system can be applied for other real time scenarios such as hospitals, children safety, security systems, etc. To increase the response time during action recognition, one can implement the system using parallel programming.

Acknowledgment

Authors are thankful to the anonymous

Acknowledgment

Authors are thankful to the anonymous reviewers for their expert and valuable comments on work. Authors are also thankful to PICT students on which College Corridor scenario dataset is created.

References

[1] Aggarwal, J. K., & Ryoo, M. S. (2011). Human activity analysis: A review. *ACM Computing Surveys (CSUR)*, *43*(3), 16.

[2] Kale, G. V., & Patil, V. H. (2016). A study of vision based human motion recognition and analysis. *International Journal of Ambient Computing and Intelligence (IJACI)*, *7*(2), 75-92.

[3] Tran, D., & Sorokin, A. (2008, October). Human activity recognition with metric learning. In *European conference on computer vision* (pp. 548-561). Springer, Berlin, Heidelberg.

[4] Arikan, O., Forsyth, D. A., & O'Brien, J. F. (2003, July). Motion synthesis from annotations. In *ACM Transactions on Graphics (TOG)* (Vol. 22, No. 3, pp. 402-408). ACM.

[5] Zhang, H., & Yoshie, O. (2012, July). Improving human activity recognition using subspace clustering. In *2012 International Conference on Machine Learning and Cybernetics* (Vol. 3, pp. 1058-1063). IEEE.

[6] Kailing, K., Kriegel, H. P., & Kröger, P. (2004, April). Density-connected subspace clustering for high-dimensional data. In *Proceedings of the 2004 SIAM international conference on data mining* (pp. 246-256). Society for Industrial and Applied Mathematics.

[7] Belongie, S., Malik, J., & Puzicha, J. (2002). Shape matching and object recognition using shape contexts. *IEEE Transactions on Pattern Analysis & Machine Intelligence*, (4), 509-522.

[8] Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints. *International journal of computer vision*, *60*(2), 91-110.

[9] Niebles, J. C. (2007, June). A hierarchical model of shape and appearance for human action classification. In *2007 IEEE Conference on Computer Vision and Pattern Recognition* (pp. 1-8). IEEE.

[10] Palaniappan, A., Bhargavi, R., & Vaidehi, V. (2012, April). Abnormal human activity recognition using SVM based approach. In *2012 International Conference on Recent Trends in Information Technology* (pp. 97-102). IEEE.

[11] Iqbal, J. M., Lavanya, J., & Arun, S. (2015). Abnormal Human Activity Recognition using Scale Invariant Feature Transform. *International Journal of Current Engineering and Technology*, *5*(6), 3748-3751.

[12] Laaksonen, J., & Oja, E. (1996, June). Classification with learning k-nearest neighbors. In *Proceedings of International Conference on Neural Networks (ICNN'96)* (Vol. 3, pp. 1480-1483). IEEE.

[13] Ravi Babu, U., & Venkateswarlu, Y. (2014). Aneel Kumar Chintha,"Handwritten Digit Recgnition using K-Nearest Neighbout Classifier", IEEE. In *World Congress on Computing and Communication Technologies* (pp. 60-65).

[14] Ann, O. C., & Theng, L. B. (2014, November). Human activity recognition: a review. In *2014 IEEE International Conference on Control System, Computing and Engineering (ICCSCE 2014)* (pp. 389-393). IEEE.

[15] Subetha, T., & Chitrakala, S. (2016, February). A survey on human activity recognition from videos. In *2016 International Conference on Information Communication and Embedded Systems (ICICES)* (pp. 1-7). IEEE.

[16] Chaquet, J. M., Carmona, E. J., & Fernández-Caballero, A. (2013). A survey of video datasets for human action and activity recognition. *Computer Vision and Image Understanding*, *117*(6), 633-659.

[17] Hsu, C. W., & Lin, C. J. (2002). A comparison of methods for multiclass support vector machines. *IEEE transactions on Neural Networks*, *13*(2), 415-425.

[18] Chang, C. C., & Lin, C. J. (2011). LIBSVM: a library for support vector machines. *ACM transactions on intelligent systems and technology (TIST)*, *2*(3), 27.

[19] Chen, C., Jafari, R., & Kehtarnavaz, N. (2015, September). UTD-MHAD: A multimodal dataset for human action recognition utilizing a depth camera and a wearable inertial sensor. In *2015 IEEE International conference on image processing (ICIP)* (pp. 168-172). IEEE.

[20] S. Tasdemir, Artificial Neural Network Model For Prediction Of Tool Tip Temperature And Analysis, International Journal of Intelligent Systems and Applications in Engineering, 2018, 6(1): 92-96.

[21] C. Aci, C. Ozden, Prediction The Severity Of Motor Vehicle Accident Injuries In Adana-Turkey Using Machine Learning Methods And Detailed Meteorological Data, International Journal of Intelligent Systems and Applications in Engineering, 2018, 6(1): 72-79.

[22] F. Khademi, Predicting strength of recycled aggregate concrete using artificial neural network, adaptive neuro-fuzzy inference system and multiple linear regression, Int. J. Sustain. Built Environ. 5 (2), (**2016**) 355–369, doi: 10.1016/j.ijsbe.2016.09.003.

[23] F. Khademi, M. Akbari, S.M. Jamal, Prediction of compressive strength of concrete by data-driven models, i-manager's J. Civ. Eng. 5 (2), (**2015**), 16.

[24] M. Nehdi, M. Bassuoni, Fuzzy logic approach for estimating durability of concrete, Proc. Ins. Civ. Eng.-Constr. Mater. 162 (2) (**2009**) 81–92, doi: 10.1680/coma.2009.162.2.81.

[25] B. Vakhshouri, S. Nejadi, Predicition of compressive strength in light-weight self-compacting concrete by ANFIS analytical model, Arch. Civ. Eng. 61 (2), (**2015**) 53–72, doi:10.1515/ace-2015-0014.

[26] I. Mansouri, Predicting behavior of FRP-confined concrete using neuro fuzzy, neural network, multivariate adaptive regression splines and M5 model tree techniques, Mater. Struct. 49 (10), (**2016**) 4319–4334, doi: 10.1617/s11527-015-0790-4.

[27] A. Sadrmomtazi, J. Sobhani, M. Mirgozar, Modeling compressive strength of EPS lightweight concrete using regression, neural network and ANFIS, Constr. Build. Mater. 42, (**2013**), 205–216, doi: 10.1016/j.conbuildmat.2013.01.016.

[28] EN 197-1. Cement - Part 1: Composition, specifications and conformity criteria for common cements, 2011.