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GOAT FLOCK SURVEILLANCE: A VIDEO ANALYTICS FRAMEWORK USING QUADCOPTER

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ABSTRACT: In the present study, goat flock surveillance algorithm using video analytics was determined. The surveillance video camera was mounted over a quadcopter camera, which captured the videos of flocks. A video analytics algorithm using Haar features and the Ada Boost classifier was performed. The technique for tracking of flocks is based on the Kanade-Lucas-Tomasi feature (KLT) tracker. The algorithm presented here allows goat flock surveillance without human guidance and was helpful in real-time monitoring and management of goat flocks. The proposed algorithm made monitoring of goat flocks economical and could be applied to any kind of animal flock in different environments. The qualitative and quantitative analysis carried out for successful goat detection demonstrated the efficiency of the proposed algorithm as compared to the state-of-the-art goat flock surveillance and detection algorithms. The proposed algorithm successfully tracked the goat with accuracy of 93%.

Keywords: Animal detection, Haar transform, Ada Boost, Kanade-Lucas-Tomasi and Quadcopter.

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INTRODUCTION

The management and monitoring of goat flocks requires considerable efforts. This involves labor, effort and time. Goat flocks generally herd in free areas such as forests and mountains. The herding of goat flocks is a common practice in many areas of Pakistan: in central Sindh and the Northern areas of Baluchistan (Nayak, 2014).

Traditionally goat farming is mostly done in a wildlife environment. A wildlife environment has advantages and disadvantages for the animals living there (Siewiorek, 2012). Goat farming is a big business as it is used for breeding, and for meat and milk production. Thus, losses can be costly. Losses occur due to hunting by animals and hunters. Goats can fall into pools of water and drown or can be killed by landslides or falling trees. Floods can also result in the death of goats (Mednis *et al.*, 2012).

There are other circumstances that also pose a threat to their lives, dangerous diseases such as enterotoxaemia, foot rot and listeriotic (Kays *et al.*, 2015). In order to protect the goats from these threats and dangers. An automated monitoring mechanism is needed. No such algorithm has yet been developed for goat activity monitoring in an uncontrolled environment (Mathanker *et al.*, 2011). A typical example for a controlled setting is a monitoring application in which the camera is usually fixed and the background is mostly static. In such a scenario, a background model could be learned and objects of interest could be identified by detecting changes to the background. However, the video material investigated in this work do not provide a well-defined setting (Cancellaro *et al.*, 2011).

Quadcopters mounted with camera are used for monitoring the flock's activities in the open environment (Khemiri *et al.*, 2012). The frames of video captured by the quadcopter camera are analyzed. During the frame-by-frame analysis, animal detection is performed. After animal detection, animal tracking is carried out. On the basis of tracking, different reports are generated for end user analysis and actions (Nayak, 2014; Othman and Shazali, 2012). The monitoring of flocks is of great importance for the safety of these animals. While many technological solutions have been proposed in the past decade, each solution has certain benefits and shortcomings (Nayak, 2014; Othman and Shazali, 2012). The tags are attached to the goat ears. These tags contain the ID information of each goat. This helps in protecting the goat from theft and other hazards. These methods have limitations, however, the reader should be in a detectable frequency range so that it could detect the tags (Guzman-Zavaleta *et al.*, 2014).

Video camera-based surveillance is one solution for such situations. The camera system can capture video of the flock in open fields. The limitation of this method is that the flock has to remain within range of the camera. This solution is suitable for limited areas such as farms, where the area is defined. For large farms, multiple cameras can cover the whole area of the farm and provide surveillance for the area. However, the same solution cannot be applied to the open environment situation (Feng *et al.*, 2014). A camera-mounted quadcopter can be used for the video capturing of the flock. After the quadcopter captures the video, it is then analyzed. After analysis, the quadcopter can be given commands to track the flock (Stowell *et al.*, 2013).

According to a study of the video analytics of goat movement, a large amount of videos from trips into the field and in a wildlife environment are required for better analysis of the results. These videos are stored in a cloud server-based environment. Wildlife videos are large, and monitoring activity from them is time-consuming (Manzo-Martinez and Camarena-Ibarrola, 2013).

Contrary to above discussion, a goat could be left behind from the flock while herding. For such situations, there should be an algorithm that is not only able to detect the goats in the uncontrolled environment but also to monitor their activities, and also generate an alarm when sensing a threat. Hence, a novel algorithm is presented that performs quadcopter video analytics for the safety of goats in an uncontrolled environment.

MATHERIALS AND METHODS

Goat flock and farming monitoring was performed in an uncontrolled environment where there were no boundaries and where a wildlife environment was provided.

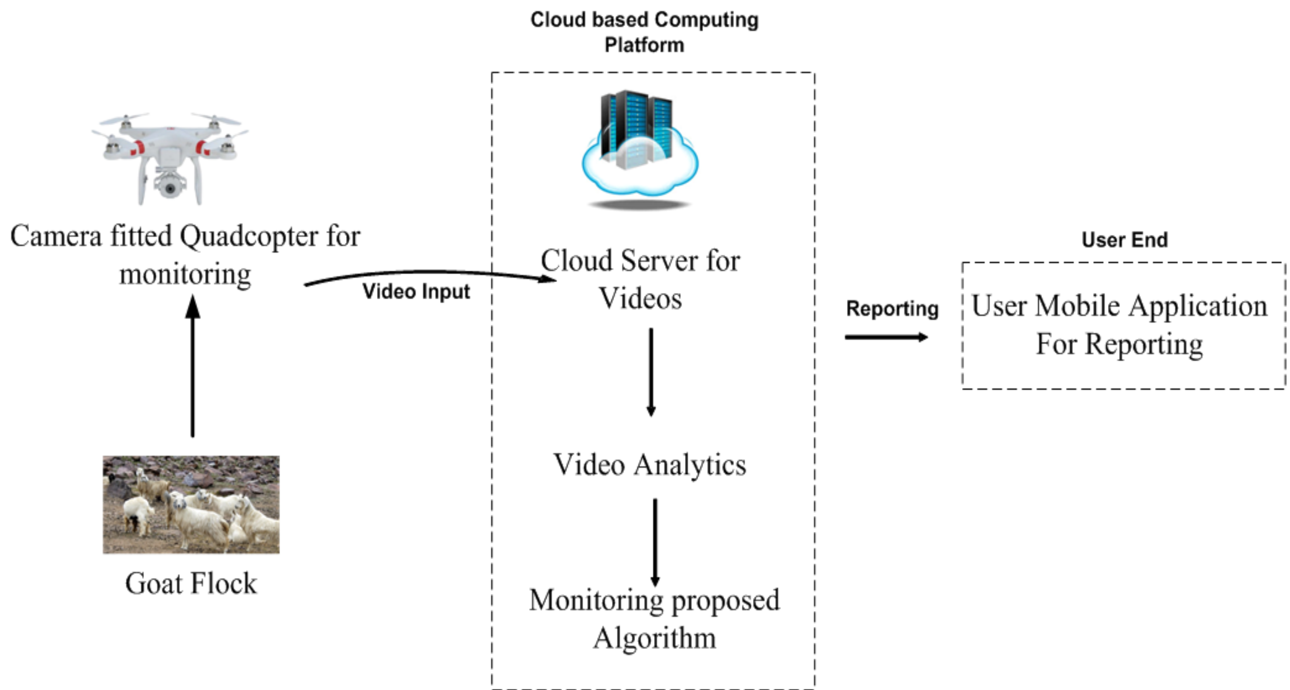

Figure-1: Block diagram of quadcopter-based goat monitoring system

Figure 1 shows the complete setup diagram of the proposed algorithm. Video input taken from the quadcopter with camera was saved as backup in the cloud-based server for future analysis and tracking. As the video was saved in the cloud server, an alert alarm was generated for taking the precautionary measures. The scenario and video was saved frame by frame in the server for future analysis and saving processing time. Alarm was generated in 5ms after mysterious activity was observed. Each frame of the video was analyzed and tracked. As evidence, tracked reports were generated from the video analyzed and transferred to the end user for actions over the mobile like agritecsoft, easy keeper, uniform goat, sigaruminant, goat manager 007 and Maryland. The camera fitted on the quadcopter was connected wirelessly with the cloud server for saving the videos. Videos from the cloud server were accessed by the video analytics algorithm (Ramanan and Forsyth, 2003). During video analytics, activity monitoring m of the goats at the time t for the region r was performed as under:

$$m(t+1) = \left[(r, 1, \tau) \quad \begin{bmatrix} c(t) \\ m(t) \\ d(t) \end{bmatrix} \right] \qquad (1)$$

Where c, m and d were matrices of video which was monitored. τ was angle of goat at which it observed. During activity monitoring, a machine learning algorithm applied in order to train the algorithm. If any mysterious activity is monitored, the alarm would be generated to the user's (farmer's) application on a mobile / computer. Figure 2 explained the steps of video analytics and activity monitoring. Video was processed frame by frame. Each frame was monitored separately.

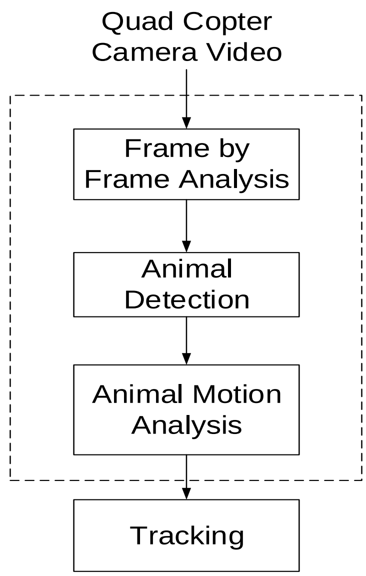

Figure-2: Block diagram of Video Analytics

The sequence of monitoring results lead to the results compilation. In the first step, the video frame was passed as input to the proposed algorithm. From the frame, the detection of a goat was performed initially. After successful detection, activity monitoring of the goats was performed. For activity monitoring, an algorithm was trained using different machine learning algorithms for different activities and under different conditions. For tracking purposes, Kanade-Lucas-Tomasi (KLT) feature was used (Cancellaro *et al.*, 2011; Mathanker *et al.*, 2011).

After monitoring, results were compiled and produced. Alarm was generated if any mysterious activity observed in the goat flock. Figure 3 explained the generic activity monitoring algorithms applied in the proposed algorithm. There were n number of input cameras that were monitoring at the same time and motion detection was performed. After motion detection, frame-by-frame tracking was processed. After that, all camera input underwent field-of-view FOV fusion. In the last step, different machine learning algorithms were applied with fusion for the activity detection of the goat flock (Dalal and Triggs, 2005).

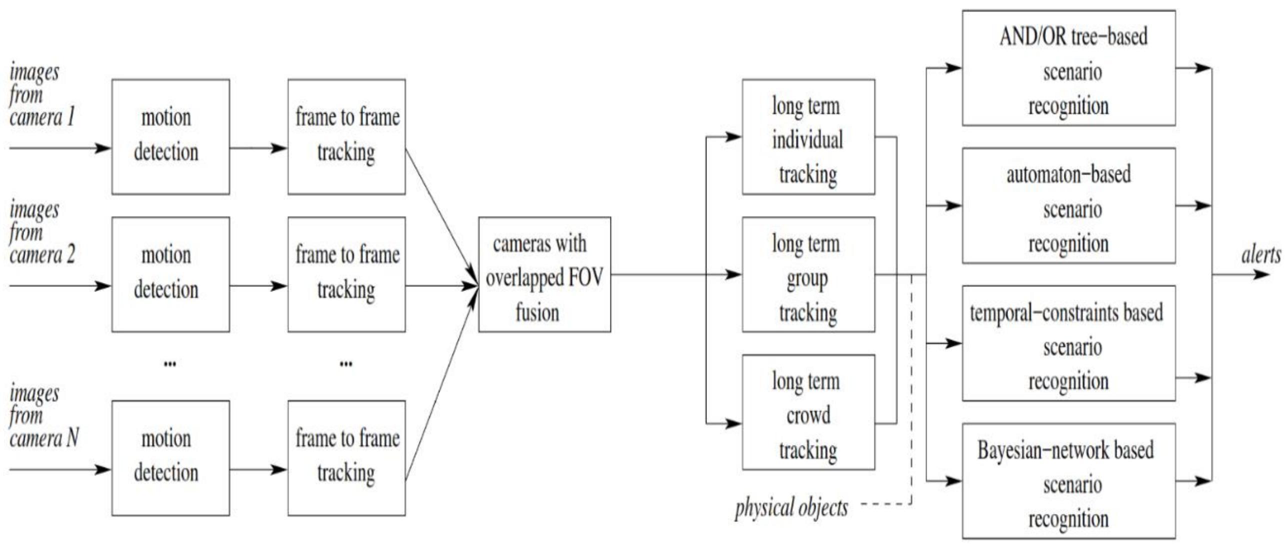

Figure-3: Block diagram of algorithmic architecture

The quadcopter used in the state-of-the-art algorithm was monitored using application. The movement of quadcopter was controlled using the satellite GPS maps (Brown *et al.*, 2013; Othman and Shazali, 2012). The quadcopter was given a map over which hovers and monitors the goat flock from danger zone. The given map was saved in the database for future analysis and saving of loading time for future.

RESULTS AND DISCUSSION

The input setup used consisted of three of quadcopters fitted with wireless video cameras for covering 360° complete view and monitored the activities of goats in the forest. Figure 4 showed the pictorial representation of a setup that included a quadcopter with a camera and goat watching flying quadcopter activity. The white rectangular box represents the quadcopter while the red rectangular box highlights the goat as shown in fig. (4).

Figure-4: Red color rectangle marking shadow of quadcopter with camera. White color rectangle marking goat-watching copter

First of all, the goat was detected from the input frames of 3 cameras fitted to quadcopters. The detection was performed using the Haar Transform (Kays *et al.*, 2015) and the Viola and Jones algorithm fusion (Everingham and Zisserman, 2004). Detection was represented by red boxes as shown in fig. (4), fig. (5), and fig. (6), respectively, which clearly indicated the detection of goat, motion detection as well as activity monitoring.

The detection and tracking of goats and animals was actually tracked in the form of reports for actions to be performed. These reports were of different forms depending on criteria and conditions.

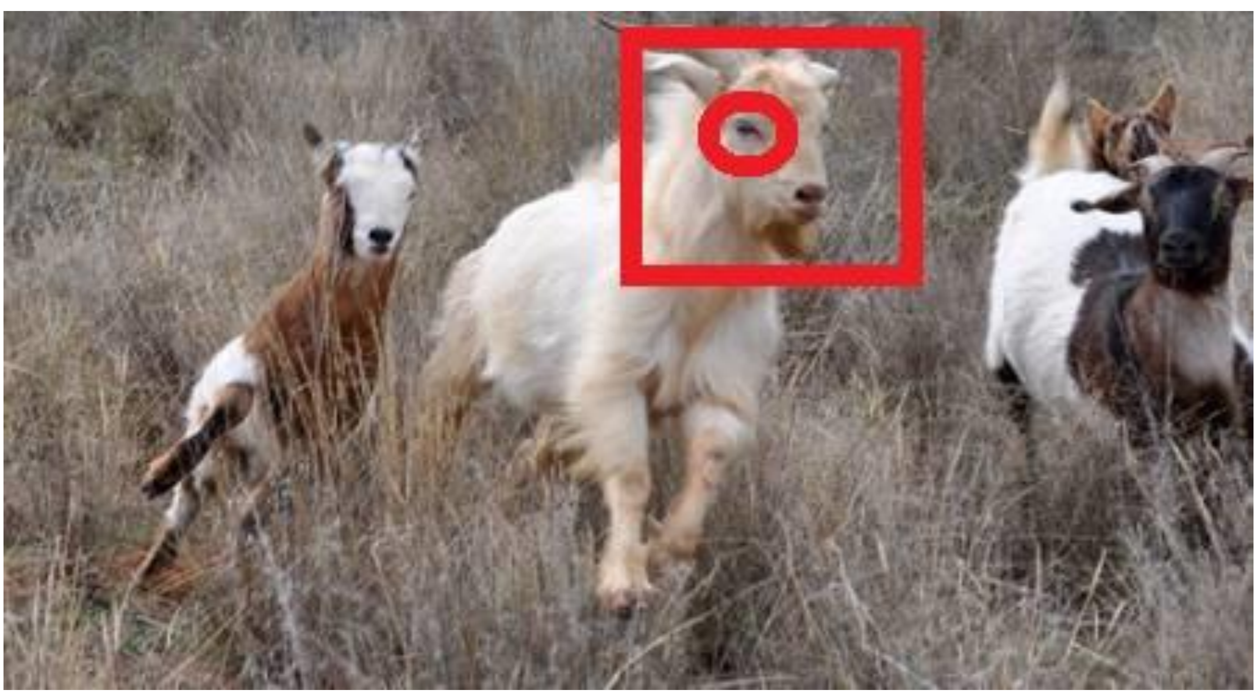

Figure 5: Goat motion detection and monitoring

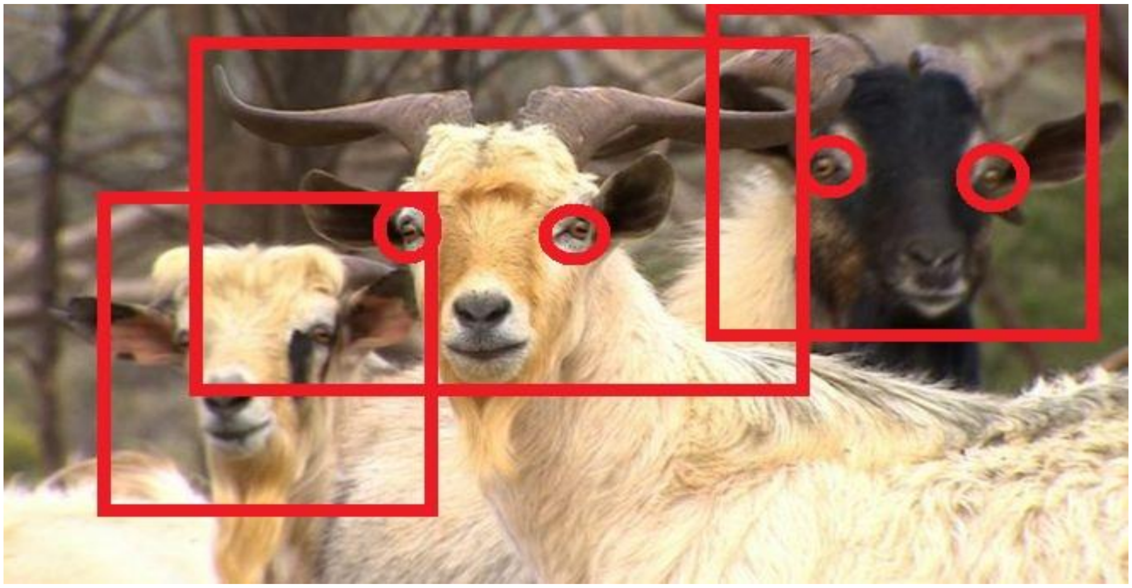

Figure-6: Goat detection and motion detection and monitoring

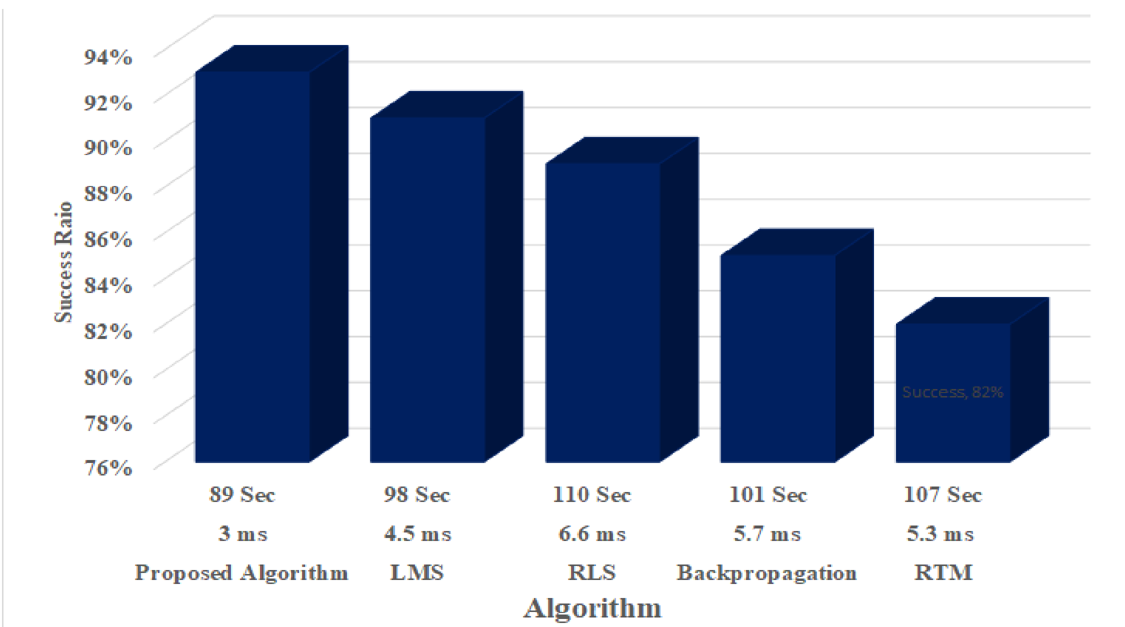

Figure-7: Performance evaluation of proposed algorithm with developed algorithms

It was observed that, state-of-the-art algorithm tracked the goat in 89sec with transmission of alert in 3ms (Qu *et al.*, 2017; Long *et al.*, 2014). Whereas, LMS tracked the goat in 98sec, RTM tracked the goat in 107sec and backpropagation tracked in 101sec. All these algorithms were experimented over the standard dataset of video for accuracy measurement of monitoring and tracking. It is observed that, state-of-the-art algorithm tracked the goat with 93%, whereas LMS detected with accuracy of 91%, backpropagation 85% and RTM 82% (Boval and Dixon, 2012). Alarm was generated with different time delay in least mean square (LMS), reverse time migration (RTM) and backpropagation algorithms. The proposed state-of-the-art algorithm generated alarm in 3ms after gathering information in 89sec. whereas previous algorithms generated alarm with greater delay as showed in fig. (7). Quadcopter used GPS in the state-of-the-art proposed algorithm for tracking the position and location of goat and flock (Mednis *et al.*, 2012). The proposed algorithm was implemented for end user android application of a mobile for the desired actions (Hays *et al.*, 2016). Figure 8 showed the GPS-based location tracked over the mobile for goat flock monitoring and tracking (Ramanan and Forsyth, 2003).

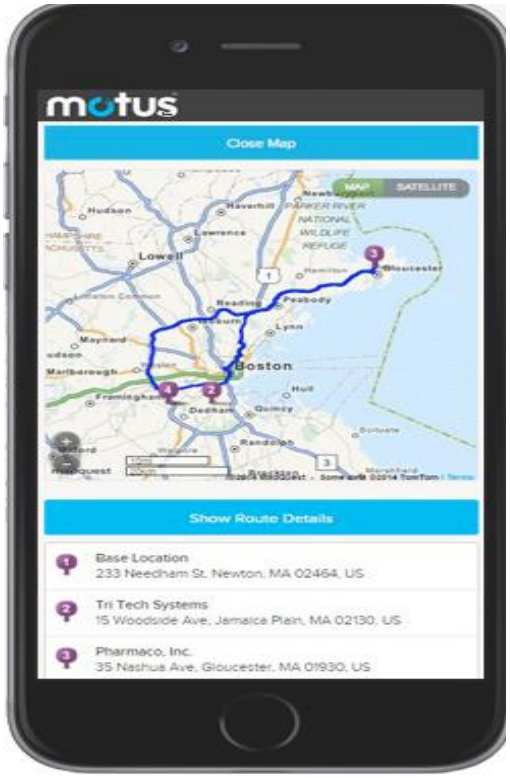

Figure-8: GPS location of goats on mobile

Similarly, Figure 9 gave a brief overview of an application developed for a goat activity monitoring and tracking system. The menu contains guards, weather, danger, hazards, live video, map chat and backup, etc. Weather tells the weather conditions of the flock area. On the basis of weather updates, guards were given the task of taking action using the guard's menu. The location of goat was obtained from maps using GPS satellite tracking system. The danger and hazards menu informed about different hazards or dangers at the specific time to the flock of goat.

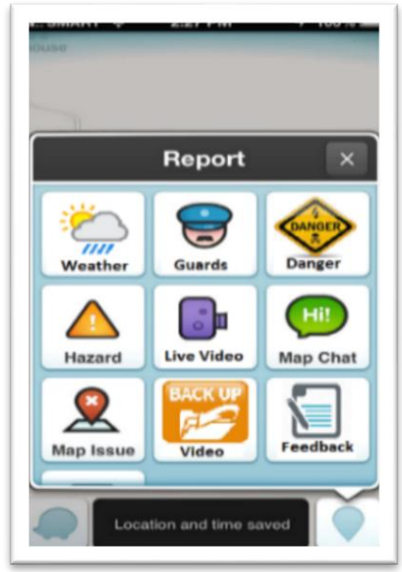

Figure-9: Overview of android-based reporting application

The following danger and hazards were observed:

1. Goat found away from the flock or left behind the flock
2. Goat reached near water area
3. Goat reached near the edge of hill
4. Goat found near the fence area

These hazards and dangers were detected by the video analytics.

Goat flock monitoring was successfully achieved using the proposed algorithm. Previously developed algorithms focused on either tracking or monitoring (Bhardwaj *et al.*, 2017; Ramakrishnan *et al.*, 2017). Actual results of different motion detection frames processed for compilation of activity monitoring. The detection performed from frontal view as well as from the side view. Different states of the goat under different conditions were processed and stated in table 1 with different number of behaviors monitored. The success rate observed was above 80%. The accuracy of the overall process of activity monitoring and goat detection was 80%. In some cases, the recognized hits were not 100% due to environmental conditions and the limitations of the system.

Table-1. Technical validation analysis of activity monitoring

States	No. of behaviors	True hits	% of success	Accuracy	False hits
Running	10	8	80%	65%	1
Standing	15	15	100%	100%	0
Eating Grass	7	5	71.42%	77%	0
Jumping	9	8	88.88%	86.6%	2
Total	41	36	87.8 %	80%	3

The processing time and accuracy improved in the proposed algorithm from the already developed algorithms. Table (2) explained the processing time and accuracy comparison with previous algorithms.

Table-2. Processing time and accuracy comparison

Algorithm	Classification model	State	Accuracy	Time (sec.)
Proposed model	KLT and Haar Transform	Front and side	89%	5
LMS	Haar Transform	Front	85%	8
RLS	KLT	Top	81%	7
Backpropagation	Fourier Transformation	Front	78.88%	6

The Table 2 expressed, proposed state-of-the-art algorithm classified the targeted goat flock with accuracy of 89% in 5sec (Bilandžić *et al.*, 2017; De Liberato *et al.*, 2018; Malesios *et al.*, 2017). The proposed model used KLT and Haar transform for detecting the goat from front and side poses whereas LMS only succeed for the front view using Haar transform for classification (Haile *et al.*, 2017; Tsiplakou *et al.*, 2017; Ventura-Cordero *et al.*, 2017). The LMS classified with up to 85% and RLS just classified the goat with accuracy of 81% for top view only in 6 sec (Mehmood *et al.*, 2016; Mehmood *et al.*, 2018; Mehmood *et al.*, 2018).

The present analysis of the flock surveillance algorithms using the video analytics indicated that surveillance and monitoring of flock was of great importance for the safety of animal's life. State-of-art algorithms were compared with previous developed systems. In fig (6), the white box for quadcopter and red box for the goat detected in the forest. The performance evaluation of the proposed algorithm with state-of-the-art algorithms presented in graphical form in fig (9).

It was observed that, proposed algorithm achieved the accuracy of 93% with alert generation in 3ms. The proposed algorithm performed detection in 89sec. Tongue (2017) examined LMS for goat detection which was performed in 98sec. According to Tongue (2017), accuracy achieved by the LMS was 91% for animal detection and tracking. Caruso, Suarez and Joulie (2017) reported that RLS used for animal motion detection and tracking was performed in 110sec with 89% accuracy in tracking. Gillman (2017) worked on animals' detection and monitoring and found that animal detection could be performed in 101sec with 85% accuracy in detection using backpropagation algorithm.

The proposed algorithm performed the detection under environmental conditions. We have tested the proposed algorithm in sunny day environment, rainy season and cloudy environment as well. Proposed algorithm successfully detected the goat, which needed the attention for safety from flock.

Conclusion: The proposed algorithm made it easier for farmers to take care of their goats and to avoid risks in uncontrolled environments and also capable of successfully detecting goats in open fields. The stored videos on the cloud can be further analyzed by applying video analytics algorithms to provide further guidance about hazards that these flocks may face.

REFERENCES

Bhardwaj, B., R. Chahota, S. Gupta, P. Malik and M. Sharma (2017). Identification of chlamydial strains causing abortions and pneumonia in sheep and goat flocks during trans Himalayan seasonal migration in the northern region of India. Veter Arh. 87(2): 151-170.

Bilandžić, N., I. Varenina, B.S. Kolanović, D.B. Luburić, I. Varga, B. Želježić, L. Cvetnić, M. Benić, S. Tanković and Z. Cvetnić (2017). Occurrence of aflatoxin M1 in raw cow, goat and sheep milk during spring and autumn in Croatia during 2016. Toxin. Rev. 36(2017): 290-296.

Boval, M. and R. Dixon (2012). The importance of grasslands for animal production and other functions: a review on management and methodological progress in the tropics. Anim. 6(5): 748-762.

Brown, D.D., R. Kays, M. Wikelski, R. Wilson and A.P. Klimley (2013). Observing the unwatchable through acceleration logging of animal behavior. Anim. Biol. 1(1): 1-20.

Cancellaro, M., F. Battisti, M. Carli, G. Boato, F.G. De-Natale, and A. Neri (2011). A commutative digital image watermarking and encryption method in the tree structured Haar transform domain. Sig. Img. Proc. Comm. 26(1): 1-12.

Caruso, M., L. Latorre, G. Santagada, R. Fraccalvieri, A. Miccolupo, R. Sottili, L. Palazzo and A. Parisi (2016). Methicillin-resistant Staphylococcus aureus (MRSA) in sheep and goat bulk tank milk from Southern Italy. Sm. Rumn. Res. 135(1): 26-31.

Dalal, N. and B. Triggs (2005). Histograms of oriented gradients for human detection. IEEE Comp. Soci. Conf. 1(1): 886-893.

De Liberato, C., R. Frontoso, A. Magliano, A. Montemaggiori, G.L Autorino, M. Sala, A. Bosworth and M.T. Scicluna (2018). Monitoring for the possible introduction of Crimean-Congo haemorrhagic fever virus in Italy based on tick sampling on migratory birds and serological survey of sheep flocks. Prev. Vet. Med. 149(1): 47-52.

Everingham, M. and A. Zisserman (2004). Automated person identification in video. Int. Conf. on Img. Vid. Ret. 3115(1): 289-298.

Feng, P., M. Yu, S.M. Naqvi, and J.A. Chambers (2014). Deep learning for posture analysis in fall detection. Int. Conf. Dig. Sig. Proc. 3(2): 12-17.

Guzman, Z.Z.J., C.F. Uribe, A. Menendez-Ortiz, and J.J. Garcia-Hernandez (2014). A robust audio fingerprinting method using spectrograms saliency maps. Int. Conf. Internet. Tech. Sec. Transa. 1(1): 47-52.

Haile, A., H. Hassen, H. Gatew, T. Getachew, R. Lobo and B. Rischkowsky (2017). Investigations into nematode parasites of goats in pastoral and crop livestock systems of Ethiopia. Invest. Trop. Animal Health Prod. 50(3): 643-650.

Hays, G.C., L.C. Ferreira, A.M. Sequeira, M.G. Meekan, C.M. Duarte, H. Bailey, F. Bailleul, W.D. Bowen, M.J. Caley and D.P. Costa (2016). Key questions in marine megafauna movement ecology. Trends Eco. Evol. 31(6): 463-475.

Joulie, A., E. Rousset, P. Gasqui, E. Lepetitcolin, A. Leblond, K. Sidi-Boumedine and E. Jourdain (2017). Coxiella burnetii circulation in a naturally infected flock of sheep: individual follow-up of antibodies in serum and milk. App. Environ. Micro. 83(13): 1-11.

Kays, R., M.C. Crofoot, W. Jetz, and M. Wikelski (2015). Terrestrial animal tracking as an eye on life and planet. Sci. 348(6240): 1-12.

Khemiri, H., D. Petrovska-Delacretaz and G. Chollet (2012). A Generic Audio Identification System for Radio Broadcast Monitoring Based on Data-Driven Segmentation. Int. Symp. Multimedia. 4(1): 427-432.

Long, J.A., T.A. Nelson, S.L. Webb and K.L. Gee (2014). A critical examination of indices of dynamic interaction for wildlife telemetry studies. J. Ani. Eco. 83(5): 1216-1233.

Malesios, C., P. Kostoulas, K. Dadousis and N. Demiris (2017). An early warning indicator for monitoring infectious animal diseases and its application in the case of a sheep pox epidemic. Stoch. Environ. Res. Risk. Assess. 31(2): 329-337.

Manzo-Martinez, A. and A. Camarena-Ibarrola (2013). An eigenvalues analysis with entropy-per-chroma feature. IEEE Int. Meet. Pow. Elect. Comp. 4(1): 1-6.

Mathanker, S., P. Weckler, T. Bowser, N. Wang and N. Maness (2011). Adaboost classifiers for pecan defect classification. Comp. Elect. Agri. 77(1): 60-68.

Mednis, A., A. Elsts, and L. Selavo (2012). Embedded solution for road condition monitoring using vehicular sensor networks. Int. Conf. App. Info. Comm. Tech. 4(1): 1-5.

Mehmood, Z., S.M. Anwar, N. Ali, H.A. Habib and M. Rashid (2016). A novel image retrieval based on a combination of local and global histograms of visual words. Hindawi, Math. Prob. Engg. 2016(2016): 1-12.

Mehmood, Z., S.M. Anwar and M. Altaf (2018). A novel image retrieval based on rectangular spatial histograms of visual words. K. J. Sci. 45(1): 54-69.

Mehmood, Z., T. Mahmood and M.A. Javid (2018). Content-based image retrieval and semantic automatic image annotation based on the weighted average of triangular histograms using support vector machine. AI. 48(1): 166-181.

Nayak, N.M. (2014). Graphical Models for Wide-Area Activity Analysis in Continuous Videos. Uni. of. Calfon. (USA). 240 p.

Othman, M.F. and K. Shazali (2012). Wireless sensor network applications: A study in environment monitoring system. Proc. Engg. 41(2012): 1204-1210.

Qu, H., T. Zheng, L. Pang and X. Li (2017). A new detection and recognition method for optical fiber pre-warning system. Optik-Int. J. Light. Elec. Optics. 137(2017): 209-219.

Ramakrishnan, M., R. Santhamani and A. Pandey (2017). Capripox outbreak in a mixed flock of sheep and goats in India. Trans. Emerg. Dis. 64(1): 27-30.

Ramanan, D. and D.A. Forsyth (2003). Using Temporal Coherence to Build Models of Animals. IEEE. 4(1): 338-345.

Stowell, D., S. Musevic, J. Bonada and M.D. Plumbley (2013). Improved multiple birdsong tracking with distribution derivative method and Markov renewal process clustering. IEEE Acout. Sp. Sig. Proc. 4(1): 468-472.

Suarez, V.H., G.M. Martínez, A.E. Viñabal and J.R. Alfaro (2017). Epidemiology and effect of gastrointestinal nematodes on dairy goats in Argentina. Ond. J. Vet. Res. 84(2): 1-5.

Tsiplakou, E., M. Chatzikonstantinou, C. Mitsiopoulou, C. Karaiskou, A. Mavrommatis, K. Sotirakoglou, N. Labrou and G. Zervas (2017). Effect of soya bean and fish oil inclusion in diets on milk and plasma enzymes from sheep and goat related to oxidation. J. Ani. Phy. Ani. Nut. 101(4): 733-742.

Ventura, C.J., P.G. Pech, J.T. Acosta, C.S. Castro and J.T. Garrido (2017). Sheep and goat browsing a tropical deciduous forest during the rainy season: why does similar plant species consumption result in different nutrient intake. Ani. Proc. Sci 54(2): 99–113.