Unsupervised Abnormality Detection Using Heterogenous Autonomous System

Kazi Mejbaul Islam¹, Rouhan Noor², Sayeed Shafayet Chowdhury³, Tafanunm Tahiat Ohi⁴, Mohammad Redwan Islam⁵, Chinmoy Kumer Roy⁶, Nazmus Sakib⁷

¹,²,⁴,⁵,⁶,⁷ Dept. of EEE, Ahsanullah University of Science and Technology, ³Dept. of ECE, Purdue University

Abstract—Due to the rise of autonomous vehicles like drones and cars anomaly detection for better and robust surveillance becomes prominent for real-time recognition of normal and abnormal states. But the whole system fails if the unmanned device is unable to detect its own device’s anomaly in real-time. Considering the scenario, we can make use of various data of autonomous vehicles like images, video streams, and other digital or analog sensor data to detect device anomaly. In this paper, we have demonstrated a heterogeneous system that estimates the degree of an anomaly in unmanned surveillance drone by inspecting IMU (Inertial Measurement Unit) sensor data and real-time image in an unsupervised approach. We’ve used AngleNet for detecting images taken in an abnormal state. On top of that, an autoencoder fed by the IMU data has been ensemble with AngleNet for evaluating the final degree of the anomaly. This proposed method is based on the result of the IEEE SP Cup 2020 which achieved 97.3 percent accuracy on the provided dataset. Besides, this approach has been evaluated on an in-house setup for substantiating its robustness.

Keywords—Unsupervised anomaly detection, AngleNet, IMU, Drone image, Auto-encoder

I. INTRODUCTION

Machine learning has emerged as the leading technology in computer vision [1-2], biosensing [3-10], wheelchair movement [11-14], music applications [15], etc. Furthermore, the autonomous and intelligent vehicle is one of the promises of the fourth industrial revolution of machine intelligence, blockchain, and the Internet of things. Detecting abnormalities of the autonomous vehicle has become a popular research field as it’s important for providing security and ensuring the stability of the vehicle by learning and detecting abnormalities of the device by gathering sensory data [16]. Also determining normal/abnormal dynamics in a given scene from an external viewpoint is one of the emerging research fields [17-18]. Anomaly detection in both aerial and ground surveillance is an indispensable task in the contemporary world. It is getting hard to keep pace with the increasing use of surveillance cameras so device malfunction is now a regular scenario. Automatically detecting devices, the malfunction can alleviate the waste of labor and time. This paper proposes an approach for detecting device abnormalities by using intelligent and heterogeneous systems in an unsupervised manner where we determine the abnormalities of a drone that is being used for surveillance.

Since sabotage can be distinctive, it is impractical to annotate anomalous events. The Supervised method is likely to generalize specific anomalous events so to generalize other normal events, we have to use other classifiers. Also, an autonomous system deals with a diversity of data types like images and other digital or analog sensor data all of which can be useful in anomaly detection if leveraged fruitfully. So it is inefficacious and can produce more false alarm rates to different normal events[19]. Trong-Nguyen Nguyen et al. [20] proposed a deep Convolutional Neural Network that helps detect anomalies in real-time surveillance videos. He used the supervised method to train the model and as mentioned earlier it is not efficient enough. Iqbal et al. [21] proposed a method where they selected an appropriate network size for detecting abnormalities in multisensory data coming from a semiautonomous vehicle. As previous works mostly rely on a high level of supervision to learn private layer (PL) self-awareness models [22-25], Ravanbakhsh et al. [26] proposed a dynamic incremental self-awareness (SA) model which allows experiences done by hierarchical manner, starting from a simpler situation to structured one. awareness (SA) model which allows experiences done by hierarchical manner, starting from a simpler situation to a structured one. Gunale et al. [27] implemented SVM and SGD classifiers for anomaly detection in the old age home environment. One thing that should be noticed that all of these papers deal with the environmental scenario. But as mentioned earlier device anomaly is also should be taken under consideration. If the device gets damaged by any chance the arrangement of environmental anomaly detection will be hampered greatly. Also, sabotaging device is now getting popular for escaping. Keeping this in mind, the IEEE SP CUP 2020 competition [28] focuses on detecting abnormalities in the behavior of the ground and aerial systems based on embedded sensor data in real-time which is the problem addressed here.

In this paper, we use a deep Convolutional Neural Network (CNN) architecture named AngleNet [38] in a form of a Siamese Neural Network [29] to evaluate the angle difference between normal and abnormal images and we have used autoencoder for detecting anomalies in Inertial Measurement Unit (IMU) data. Finally, we ensembled all those outputs as weights and estimated the degree of abnormality of the device for a given IMU and image dataset.

This proposal uses the degree of abnormality instead of classification of any sample as normal or abnormal. The lower this value of anomaly, the closer it is to normal situations. The objectives of the paper are:

1. To detect device anomaly, we have used a modified Siamese-like regression network to estimate angle displacement between two images in a regression manner.

2. We have ensembled the anomaly of angle with the outputs of two autoencoders which are used to estimate the degree of the anomaly of two
separate IMU sensor data and calculated the overall anomaly of the drone.

The rest of this paper is arranged as follows. Section II describes the problem and also dataset description. Section III explains the proposed method where the detection methods are presented in detail. Section IV shows the experimental result and comparison and at the end Section, V concludes our work.

![Figure 1: (a) and (b) are examples of normal and abnormal images respectively](image)

II. PROBLEM AND DATASET DESCRIPTION

In SP Cup 2020, data of an unmanned drone was provided which contained data from the IMU sensor and images of respective time frames. Rosbag files are provided which contains compressed sensor data and images. Some files contained only normal time frames while other files contained both normal and abnormal time frames which are mixed. The task was to find the abnormal time frames using unsupervised methods which means we had to use only normal data for training and other calculations and using it we had to find the abnormal cases. Total of 12 Rosbag files where the total number of normal images is 277 and the number of mixed images is 392.

Besides image data, they have provided IMU sensor data. There are 6 types of data under the IMU topic name among which we have used IMU/data and IMU/mag. A total of 987 normal timestamps was provided. In IMU/data there is numerical information along 3 axes of the velocity and the orientation of the drone. On the other hand, IMU/mag has a magnetometer reading of the magnetic field. Here the detection process has two different analyses (image and IMU sensor data). An autoencoder based anomaly detection system is used for IMU data and used AngleNet to estimate the angle of the input image concerning a normal image sample and later ensembled the 3 outputs to estimate the degree of abnormality. Figure 1 shows some normal and abnormal image samples provided in this dataset and it is very clear that the angle of view is changed significantly between the two cases.

To detect an anomaly, we need to differentiate between normal and abnormal data. Since they are inherently high-dimensional, we first explore them in a lower-dimensional sub-space using PCA analysis which is shown in Figure 2. From the figure, it is evident that normal and abnormal data form separate clusters in the 2D space spanned by the first two principal component directions. This indicates that there are inherent differentiable characteristics in the normal and abnormal type of data, which we try to distinguish more vividly and accurately in the next section using our method.

![Figure 2: PCA plot of (a) IMU/data and (b) IMU/mag](image)

III. PROPOSED METHOD

From Figure 1 it is very comprehended that angle is the key difference between normal and abnormal images.

![Figure 3: Flow chart for estimating the degree of abnormality](image)

![Figure 4: Structure of AngleNet Used for angle estimation](image)
We have used AngleNet to estimate the angle between two images and used autoencoder for modeling detecting anomaly from IMU data. Figure 3 shows a flowchart we have used to combine the pipelines to form a single pipeline. We've integrated weights manually while ensembling and estimated the final degree of the anomaly. The intuition is, AngleNet can only estimate the angle, not measure it precisely and for a single timestamp, the rotation of the drone may be slightly higher than the threshold angle but the sensor data may be significantly anomalous. Also, it can happen vice versa. So it is appropriate to use weights and these are discussed further in Section IV.

A. AngleNet

In the abnormal state of a surveillance drone, it is mostly the tilt angle that varies from the normal state as depicted in Fig. 2. In normal conditions, the drone is pretty stable as shown in the dataset. While for the unstable drone, the image is tilted at a significant angle. Inspired by the Siamese network, we use AngleNet, a convolutional neural network architecture to estimate angle change from the normal state. Previously Spyros et al. [31] introduced RotNet but we can’t use this model in this case as it works in a classification manner and can only detect angles among 0, 90, 180, 270 degrees. But in AngleNet we tried to demonstrated angle estimation as a reasonable regression problem. In this model, a normal image should be provided first, and then the upcoming frames will be taken as input and the output is the angle between them. While training AngleNet, we have taken care of the case where there is any object missing and that is why AngleNet is more appropriate than [32] for our case. In Figure 4 we see the model structure where it takes two images at a size of 64x64 pixels and. On the layers, 16@64x64 denotes a tensor having 16 channels and height and a width of 64 rows and columns.

As discussed in section II, there are not much image data taken by the drone to train AngleNet in a supervised manner. To use this model in an unsupervised manner in this case, we have used the Stanford car dataset [33] to pre-train. The images were first augmented as so it can mimic the angle change, as demonstrated in Figure 5. The activation function of the final layer was relu as it is a non-negative linear function. Finally, there were 48,000 images which were divided into 80% train image and 20% validation image. Mean Squared Error was used as the loss function.

![Normal Image](image)

Figure 5: Samples of normal images and augmented images from Stanford Car Dataset

After pre-training the model using the dataset, we have fine-tuned using the provided dataset [28] to estimate the degree of abnormality \(\sigma_d\) of the images by dividing the output angle by 90.0 degrees.

B. Using Autoencoder for IMU data

An autoencoder based anomaly detection system is used for both the IMU/data and IMU/mag. We have used, similar to [34] but not exactly. The autoencoder models used here are shown in Fig. 6. While training the autoencoders, it is supposed that in an abnormal time frame, both IMU/mag and IMU/data reading are abnormal. As there is no clear description of the dataset on this issue, we have considered as such and it produced a good result in our practical experimentation which is described in Section IV-F.

![Autoencoder architecture](image)

Figure 6: Autoencoder architecture used for IMU/data and IMU/mag

As we are considering both are abnormal or normal at the same time frame, we have trained two autoencoders together. In this case, mean squared error (MSE) was considered as reconstruction loss. If L1 is the MSE for IMU/data sample and L2 is MSE for IMU/mag sample, then:

\[
Y_1 = \frac{1}{K} \sum_{i=0}^{K} (\hat{\sigma}_i - \sigma_i)^2 \quad (1)
\]

\[
Y_2 = \frac{1}{K} \sum_{j=0}^{K} (\hat{g}_j - g_j)^2 \quad (2)
\]

Where \(Y_1\) and \(Y_2\) are calculated loss for IMU/data and IMU/mag dataset respectively. \(\hat{\sigma}_i\)=ground truth of IMU/data and \(\hat{\sigma}_i\)=calculated output for the sample. Similarly, \(g_j\)=ground truth of IMU/mag data and \(g_j\)=calculated output for IMU/mag data. The total training loss is evaluated by the linear addition of the two losses \(Y_1+Y_2\). Here only the normal samples of the datasets have been used as it is unsupervised manner. The results are discussed in Section IV.

\[
Y_{\text{max, data}} \quad \text{and} \quad Y_{\text{max, mag}} \quad \text{are denotes the maximum reconstruction errors of an input from IMU/data and IMU/mag respectively. And calculated } \gamma_d, \gamma_m \text{ using (3), and (4).}
\]

\[
\gamma_d = \frac{Y_1}{Y_{\text{max, data}}} \quad (3)
\]
\[ \gamma_n = \frac{Y_2}{L_{\text{max, mag}}} \]  

(4)

IV. EXPERIMENT AND RESULT

Here the outcomes and training process of our work are discussed and compared with other works. The SP Cup competition provides a novel dataset that contains two different types of data (images and IMU sensors). So we have discussed the results individually and in the end, we have ensemble the outputs and constructed the final result.

A. IMU Anomaly Detection

The results on IMU/data and IMU/mag are discussed in Table 2. Normalization improves performance for IMU/mag as it has a wide range of data, from (-400000, 400000), it is very tough to converge the loss without normalization. The authors in [35] have claimed better accuracy than us but their system resources expensive. We are using two tiny autoencoders with the shared loss for IMU anomaly detection which can be run on common embedded devices of a low resource like raspberry pi, which is validated in subsection G. Even though their accuracy excels us, we can run our system in much lower resource having very few or no false-negative cases. If there is reported a device anomaly falsely, it is okay in this case as it will work like a false alarm with no harm for very few cases. Our proposed approach was among the top 8 performing ones in IEEE SP Cup 2020 using clustering for IMU analysis, we later improved it using autoencoder.

TABLE 1: COMPARISONS WITH OTHER ALGORITHMS

| Algorithm | Accuracy |
|-----------|----------|
| Autoencoder, Rad et. al. [36] | 96.87% |
| Kmeans Clustering, Iqbal et. al. [21] | 93.28% |
| 1D CNN, Kiranyaz et. al. [37] | 89.9% |
| PCA and Kmeans | 82.3% |
| Spectral Clustering | 91.7% |
| This paper | 97.8% |

B. AngleNet Based Anomaly Detection

Using AngleNet, we can estimate the angle between the test image and the normal image. In the abnormal images, the rotation angle is the main distinctive factor. Any images rotated by 30 degrees is supposed to be abnormal. But the threshold is perfectly tunable and user-defined. The performance of AngleNet on the test images is shown in Table 3.

TABLE 3: PERFORMANCE OF ANGLENET ON NORMAL IMAGE

| Threshold Angle | Accuracy |
|----------------|---------|
| 30 | 94.7% |
| 20 | 86.4% |

Table 3 shows the change in the accuracy level by changing the threshold angle. The state of the art image/video novelty detection algorithms is mostly for environmental anomaly detection which is not perfectly inclined with the problem we have worked with. We are more interested to find the anomaly of the device rather than the environment. Some comparisons with various methods are shown in Table 4.

TABLE 4: COMPARISON OF ANOMALY DETECTION ON IMAGE DATA

| Algorithm | Accuracy |
|-----------|----------|
| AngleNet | 94.7% |
| Optical flow supervised | 89.4% |
| Optical flow, unsupervised | 91.33% |
| Binary Classification | 84.85% |
| Autoencoder | 91.7% |

The angle is not only the difference between normal and abnormal image samples, also there is some motion factor. So we have compared the performance of anomaly detection between using optical flow and actual images. In the dataset, the provided images were sampled so they did not have a gradual movement shift among them, rather there is a rapid difference in motion and content, so optical flow did not show a good performance. Some examples of Dual TVL1 optical flow of normal and abnormal images are shown in Table 5. Here the rightmost sample is from the normal time stamp and the others are from abnormal timestamps. The image from Figure 1 (a) was used as a reference normal image to calculate all the optical flows.

TABLE 5: SAMPLES OF OPTICAL FLOW

| Image | Optical flow concerning Fig 2 (a) |
|-------|-----------------------------------|
| ![Image](image1) | ![Optical flow](optical_flow1) |
| ![Image](image2) | ![Optical flow](optical_flow2) |
| ![Image](image3) | ![Optical flow](optical_flow3) |

C. Ensembling Models

The process is designed so that both the clustering-based anomaly detection and AngleNet can be used separately or in an ensemble manner. As we have discussed we calculate the degree of abnormality in each case, ensembling them can produce a combined result. The proposed ensembling formula is given as:

\[ A = w_d \cdot \gamma_d + w_m \cdot \gamma_m + w_i \cdot \gamma_i \]  

(5)

Where the ultimate degree of abnormality is represented by A, \( w_d \), \( w_m \), \( w_i \) represents the weights for two autoencoders and one Convolutional Neural Network-based model respectively. And \( \gamma_d \), \( \gamma_m \), \( \gamma_i \) represent the degree of abnormality for IMU/data, IMU/mag, and Image respectively. To find the 3 weights, first, we considered 1 for each of them and performed extensive experiments to determine the values of the weights. The experiments have shown the combination \( w_i = 0.75 \), \( w_m = 0.9 \), and \( w_d = 1 \) provides the best results and these values were chosen for subsequent analysis. If \( A \geq 1 \), the timestamp is supposed to be abnormal.
D. Computational Cost

While training AngleNet on the Car dataset, we have used GoogleColab with Nvidia Tesla K80 GPU with 12 Gigabytes of memory. But for the testing purpose, it runs on a computer with 2 Gigabytes of GPU seamlessly. The system is tested on a system containing the Intel Core i5 processor, 8 Gigabytes of RAM, and Nvidia 940 MX. It takes 0.47 seconds on an average to process a single frame.

E. Implementation of In-house setup

For demonstrating real-time usage on an embedded device, it is used on a raspberry pi where the autoencoders ran on the pi and CNN based processing works on a remote server. The system is tested on an in-house setup, with a custom hexacopter running on Ardupilot, and used raspberry pi 3 for real-time processing and sending video frames to the server. In this setup, the accuracy of the algorithm was 96.49%.

V. CONCLUSION

In this work, we have demonstrated an unsupervised approach to detect device anomaly of an unmanned drone. An unmanned vehicle is comprised of various sensors and among those, we have used magnetometer data along with angular and linear velocity data from the Inertial Measurement Unit sensor. Besides, we have analyzed images taken by the drone in real-time and ensembled the three results for estimating the degree of an anomaly for a timestamp. As the key difference between normal and abnormal images is the rotation angle, we have sued AngleNet to detect the degree of the anomaly concerning the image. And for the IMU data, we have used an autoencoder based anomaly detection system. Finally, we have combined these results and estimated the ultimate degree of the anomaly. Rather than strictly classifying as normal or abnormal timestamp, we proposed a value that is supposed to be less than 1 if the timestamp is normal for the drone. In the future, we envision working on the effect of the adversarial attack on this system and building a proper defense mechanism.

VI. REFERENCES

[1] S. S. Chowdhury, C. Lee & K. Roy, “Towards Understanding the Effect of Leak in Spiking Neural Networks,” arXiv preprint arXiv:2006.08761 (2020).
[2] I. Garg, S. S. Chowdhury & K. Roy, “DCT-SNN: Using DCT to Distribute Spatial Information over Time for Learning Low-Latency Spiking Neural Networks,” arXiv preprint arXiv: 2010.01795 (2020).
[3] S. S. Chowdhury, R. Hyder, M. S. B. Hafiz, and M. A. Haque, “Real-time robust heart rate estimation from wrist-type ppg signals using multiple reference adaptive noise cancellation,” IEEE journal biomedical health informatics 22, 450–459 (2016).
[4] S. S. Chowdhury, M. S. Hasan, and R. Shamin, “Robust heart rate estimation from ppg signals with intense motion artifacts using cascade of adaptive filter and recurrent neural network,” in TENCON 2019-2019 IEEE Region 10 Conference (TENCON), (IEEE, 2019), pp. 1952–1957.
[5] S. A. Fattah, N. M. Rahman, A. Maksud, S. I. Foyosal, R. I. Chowdhury, S. S. Chowdhury, and C. Shahananaz, “Stetho-phone: Low-cost digital stethoscope for remote personalized healthcare,” in 2017 IEEE Global Humanitarian Technology Conference (GHTC), (IEEE, 2017), pp. 1–7.
[6] S. S. Chowdhury, S. M. A. Uddin, E. Kabir, and A. M. Chowdhury, “Detection of dna mutation, urinary diseases and blood diseases using surface plasmon resonance biosensors based on kretschmann configuration,” in 2017 International Conference on Electrical, Computer and Communication Engineering (ECCE), (IEEE, 2017), pp. 662–665.
[7] C. Shahahaz, M. J. N. Sampad, D. Adhikary, S. M. Uchayash, M. Mahdia, S. S. Chowdhury, and S. A. Fattah, “Smart hat: Safe and smooth walking assistant for elderly people,” in 2017 IEEE International Symposium on Technology and Society (ISTAS), (IEEE, 2017), pp. 1–7.
[8] S. M. A. Uddin, S. S. Chowdhury, and E. Kabir, “A theoretical model for determination of optimum metal thickness in kretschmann configuration based surface plasmon resonance biosensors,” in 2017 International Conference on Electrical, Computer and Communication Engineering (ECCE), (IEEE, 2017), pp. 651–654.
[9] S. S. Chowdhury, S. M. A. Uddin, and E. Kabir, “Numerical analysis of sensitivity enhancement of surface plasmon resonance biosensors using a mirrored bilayer structure,” Photonics Nanostuct~Fundamentals. Appl. p. 100815 (2020).
[10] S. M. A. Uddin, S. S. Chowdhury, & E. Kabir, (2020). Numerical Analysis of a Highly Sensitive Surface Plasmon Resonance Sensor for SARS-CoV-2 Detection. arXiv preprint arXiv:2008.10354.
[11] R. Hyder, S. S. Chowdhury, and S. A. Fattah, “Real-time non-intrusive eye-gaze tracking based wheelchair control for the physically challenged,” in 2016 IEEE EMBS Conference on Biomedical Engineering and Sciences (ICBES), (IEEE, 2016), pp. 784–787.
[12] S. S. Chowdhury, R. Hyder, C. Shahananaz, and S. A. Fattah, “Robust single finger movement detection scheme for real time wheelchair control by physically challenged people,” in 2017 IEEE Region 10 Humanitarian Technology Conference (R10-HTC), (IEEE, 2017), pp. 773–777.
[13] A. Maksud, R. I. Chowdhury, T. T. Chowdhury, S. A. Fattah, C. Shahananaz, and S. S. Chowdhury, “Low-cost eeg based electric wheelchair with advanced control features,” in TENCON 2017-2017 IEEE Region 10 Conference, (IEEE, 2017), pp. 2648–2653.
[14] C. Shahahaz, A. Maksud, S. A. Fattah, and S. S. Chowdhury, “Low-cost smart electric wheelchair with destination mapping and intelligent control features,” in 2017 IEEE International Symposium on Technology and Society (ISTAS), (IEEE, 2017), pp. 1–6.
[15] I. Al-Hussaini, A. I., Humayun, S. Alam, S. I. Foyosal, A. Al Masud, A. Mahmud, R. I. Chowdhury, N. Ibtehaz, S. U. Zaman, R. Hyder, and S. S. Chowdhury, (2018, April). Predictive real-time beat tracking from music for embedded application. In 2018 IEEE Conference on multimedia information processing and retrieval (MIPR) (pp. 297-300). IEEE.
[16] M. Baydoun, D. Campo, V. Sanguineti, L. Marcenaro, A. Cavallaro, and C. Regazzoni, “Learning Switching Models for Abnormality Detection for Autonomous Driving,” 2018 21st International Conference on Information Fusion (FUSION), 2018.
[17] D. Campo, A. Betancourt, L. Marcenaro, and C. Regazzoni, “Static force field representation of environments based on agents’ nonlinear motions,” EURASIP Journal on Advances in Signal Processing, vol. 2017, no. 1, 2017.
[18] V. Bastani, L. Marcenaro, and C. S. Regazzoni, “Online Nonparametric Bayesian Activity Mining and Analysis From Surveillance Video,” IEEE Transactions on Image Processing, vol. 25, no. 5, pp. 2089–2102, 2016.
[19] Waqas Sultani, Chen Chen, Mubarak Shah “Real-world Anomaly Detection in Surveillance Videos”, arXiv:1801.04264.
[20] Trong-Nguyen Nguyen, Jean Meunier DIRO, University of Montreal “Anomaly Detection in Video Sequence with Appearance-Motion Correspondence”, arXiv:1908.06351v1 [cs.CV] 17 Aug 2019
[21] H. Iqbal, D. Campo, M. Baydoun, L. Marcenaro, D. M. Gomez, and C. Regazzoni, “Clustering Optimization for Abnormality Detection in Semi-Autonomous Systems,” 1st International Workshop on Multimodal Understanding and Learning for Embodied Applications - MULEA ’19, 2019.
[22] K. Kim, D. Lee, and I. Essa, “Gaussian process regression flow for analysis of motion trajectories,” 2011 International Conference on Computer Vision, 2011.
[23] J. S. Olier, P. Martin-Plaza, D. Martin, L. Marcenaro, E. Barakova, M. Rauterberg, and C. Regazzoni, “Dynamic representations for
autonomous driving,” 2017 14th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), 2017.

[24] M. Baydoun, M. Ravanbakhsh, D. Campo, P. Marin, D. Martin, L. Marcenaro, A. Cavallaro, and C. S. Regazzoni, “a Multi-Perspective Approach to Anomaly Detection for Self-Aware Embodied Agents,” 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2018.

[25] D. Sirkin, N. Martelaro, M. Johns, and W. Ju, “Toward Measurement of Situation Awareness in Autonomous Vehicles,” Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems - CHI ’17, 2017.

[26] M. Ravanbakhsh, M. Baydoun, D. Campo, P. Marin, D. Martin, L. Marcenaro, and C. S. Regazzoni, “Hierarchy of Gans for Learning Embodied Self-Awareness Model,” 2018 25th IEEE International Conference on Image Processing (ICIP), 2018.

[27] Kishanprasad Gunale and Prachi Mukherji “An Intelligent Video Surveillance System for Anomaly Detection in Home Environment Using a Depth Camera”, Soft Computing: Theories and Applications, 473–481.

[28] “Unsupervised abnormality detection by using intelligent and heterogeneous autonomous systems,” [5] ICASSP. [Online]. Available: https://2020.ieeeicassp.org/authors/sp-cup-2020/. [Accessed: 23-Mar-2020]

[29] Gregory Koch. Siamese neural networks for one-shot image recognition. PhD thesis, University of Toronto, 2015.

[30] D. M. Ramík, C. Sabourin, R. Moreno, and K. Madani, “A machine learning based intelligent vision system for autonomous object detection and recognition,” Applied Intelligence, vol. 40, no. 2, pp. 358–375, 2013.

[31] Spyros Gidaris, Praveer Singh, Nikos Komodakis: “Unsupervised Representation Learning by Predicting Image Rotations”, 2018, arXiv:1803.07728.

[32] R. Qian, W. Li and N. Yu, “High precision rotation angle estimation for rotated images,” 2013 IEEE International Conference on Multimedia and Expo Workshops (ICMEW), San Jose, CA, 2013, pp. 1–4, doi: 10.1109/ICMEW.2013.6618298.

[33] “Cars Dataset - Stanford AI Lab.” [Online]. Available: http://ai.stanford.edu/~jkrause/car/car_dataset.html. [Accessed: 24-Mar-2020].

[34] A. Borghesi, A. Bartolini, M. Lombardi, M. Milano, and L. Benini, “Anomaly Detection Using Autoencoders in High Performance Computing Systems,” Proceedings of the AAAI Conference on Artificial Intelligence, vol. 33, pp. 9428–9433, 2019.

[35] Bahavan, Nadarasar & Suman, Navaratnarajah & Cader, Sulhi & Ranganayake, Ruwinda & Seneviratne, Damitha & Maddumage, Vinu & Seneviratne, Gershom & Supun, Yasinha & Wijesiri, Isuru & Dehgaspiyta, Suchitha & Tissera, Dumindu & Edussooryya, Chamira. (2020). Anomaly Detection using Deep Reconstruction and Forecasting for Autonomous Systems.

[36] Mohammadian Rad, Nastaran & van Laarhoven, Twan & Burlanello, Cesare & Marchiori, Elena. (2018). Novelty Detection using Deep Normative Modeling for IMU-Based Abnormal Movement Monitoring in Parkinson’s Disease and Autism Spectrum Disorders. Sensors. 18. 3533. 10.3390/s18103533.

[37] Kiranyaz, Serkan & Zafari, Morteza & Bahrami Rad, Ali & Tahir, Anas & Ince, Turker & Rudia, Hamila & Gabouj, Moncef. (2019). Real-time PCG Anomaly Detection by Adaptive 1D Convolutional Neural Networks.

[38] S. S. Chowdhury, K. M. Islam, and R. Noor, (2020). Unsupervised Abnormality Detection Using Heterogeneous Autonomous Systems. arXiv preprint arXiv:2006.03733