International Journal of Scientific Research in Computer Science, Engineering and Information Technology
ISSN : 2456-3307
OPEN ACCESS
Available Online at : www.ijsrcseit.com
doi : https://doi.org/10.32628/CSEIT2410268

Anomaly Detection Industrial Items

[1]Muhammad Owais Khan, [1]Dr. Liu Peishun, [1]Abdul Majid, [2]Dil Nawaz Hakro,[2] Basit Ali
[1]Department of Computer Science and Technology, Faculty of Information Science and Engineering, Ocean University of China
[2]Department of Software Engineering, Faculty of Engineering and Technology, University of Sindh, Jamshoro, Pakistan
Corresponding Author: Muhammad Owais Khan, aghaawaisk@gmail.com

ARTICLEINFO

Article History:

Accepted: 10 April 2024
Published: 22 April 2024

Publication Issue
Volume 10, Issue 2
March-April-2024

Page Number
729-734

ABSTRACT

Anomaly detection is one of the machines learning powered approach which identifies the various elements and objects from a big set of the data. The machine learning powered technique checks multiple objects with the help of differentiating properties and detects the objects which are dissimilar to another dataset. Anomaly detection has number of successful applications from security, medical, industrial and virtually all of the tasks which human may fail while identifying the differentiating properties. Machinery elements anomaly detection has been presented which identifies the differentiating objects of the four hundred images. Number of experiments were performed to detect the anomaly among the given 400 images. The training model has used bidirectional LSTM which gets a feature vector of twelve features, selected, and extracted with already defined algorithm. The dataset has been labelled manually and features were stored. While testing of the images, the study achieved 98% of the accuracy while detecting anomaly of the industrial elements. The system can detect anomalies in the presence of the varying colour and other properties. The accuracy can be increased by adding more images to the database and learning model more deeply. The study can be directed to various implementations including multiple learning implementations, applying on various other elements.

Keywords : Object Detection, Deep Learning, Object Tracking, Matching and Recognition, Simple Real Time Tracker.

I. INTRODUCTION

The task of identification of abnormal data which contains the differentiating features among the majority of copies or instances is called Anomalydetection [1]. Anomalydetection is one of the intention oriented research with various important applications such as the defect detection in industrial products, fault detection in infrastructure, diagnostics of medical disorders and others. Some of the other important uses of anomalydetection are finding out the system failure point(s), finding human errors, unwanted operations or deviations of environment from specified rules. Anomalydetection is considered as an important tool which can help to reduce the overall cost and risk along with providing some valuable information of failure, reason of failure, critical parts and their importance in systems under analysis. For the achievement of good performance and efficiency various learning algorithms have been employed including Auto-Encoders [4], Recurrent Neural Networks [3], Convolutional Neural Networks [2] generative adversarial networks (GAN/GANs) [4] and other deep learning methods. With the increase in data resulting complex structures, more and more deep learning algorithms are need of time to be proposed for the anomaly detection. A class imbalance problem [6] can occur once a very few abnormal samples are no abnormal samples are available in large or very large normal samples. Currently, the extensive training samples are required for the better performance of the deep anomaly detection algorithms based upon the nature of the application. Figure 1 shows the illustration of anomaly detection example.

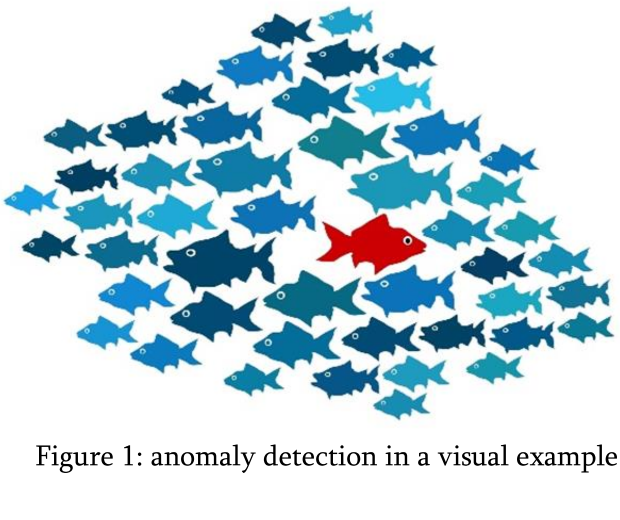

Figure 1: anomaly detection in a visual example

1.1 Types of anomaly detection

Anomaly detection can be supervised, unsupervised or the semi supervised. When a model is learning through the labelled data which explains the failures or anomalies. The other category is the unsupervised one in which the data objects are not labelled and the third category which works on the basis of small labelled data and the model performance is based on the trained data but the smaller number of labels. Most of the semi supervised and unsupervised anomaly detection is in practice due to the scarcity of labelled failure data. Figure 2 shows the point based anomaly detection and Figure 3 shows the contextual anomaly detection.

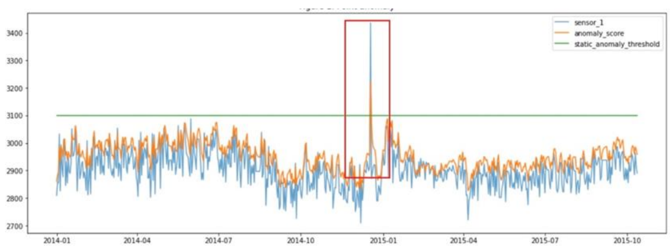

Figure 1: Contextual anomaly detection

II. LITERATURE REVIEW

For the task of detection, anomaly detection algorithms possess many of the similar terms such as the out of distribution called OOD [16], outliers [15], deviation [17] and the novelty of the images or objects [18]. Taking into general, point (s), cases, patterns, observations etc are objects which are well differentiating from a traditional data. The features are inconsistent with the well-defined data [1,10,12.19,20-22]. For example these anomaly contained objects do not confirm the same behaviour for the already defined behaviour [1], skewed from the given observations [10], or they are totally different from the given data points or even do not have similar points [23]. The types of anomalies have been categorized by the studies of [13,24] based on intrinsic properties. The study of Chalapathy et al., [12] presented the categories as point, conditional, contextual and group with correlation. The anomaly detection has been categorized in intentional and unintentional by the study of Bulusu et al., [11]. It can be inferred from these two studies that the anomaly detection can be summarized as normal samples are too similar to the other sample space whereas on the other hand the abnormal samples are too dissimilar among the normal sample space.

In the meantime, the definition has been remained an unsolved question from many of the researchers and the definition has remained conflicting and the ambiguous. The existing research [25] presented and emphasized that the outliers and the anomalies have subtle differences, but the two words have been used interchangeably in their presented review study. The other study of [26] holds the idea that the novelty also belongs to the expected or the normal region or the space, which is also the same definition for the outlier and the anomaly detection. The studies of [1] and [17] presented that it is not necessary that the novelties must be the anomaly detection, but methods used for solution are same such as novelty detection, outlier detection and anomaly detection.

Anomaly detection of Machinery Components

The anomaly detection has been experimented with the industry machines and their components. The components have been trained by the bidirectional LSTM which takes the total twelve features. The data has been created by taking the pictures rotating and changing the direction of the device. For the experiment a hundred of the images were taken into account for the database creation. The images were labelled as per convenience and in this case the current study used 400 of images of the same element by taking images from various angles by changing the angle, area, lighting mechanism and other elements. The examples of the data collected are given as under in Figure 4.

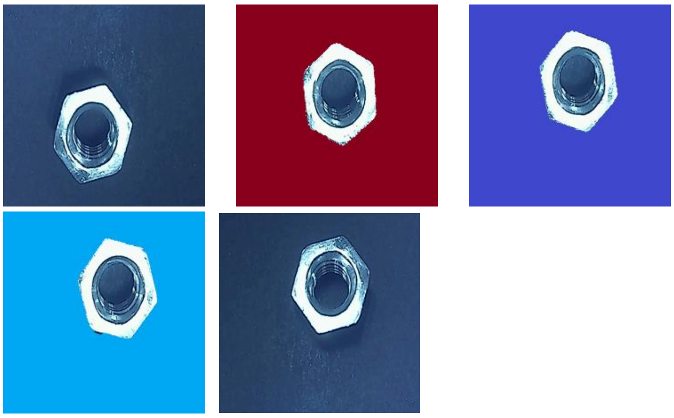

Figure 4: Trainging Data set

The machinery element has been used to create the database by varying color, orientation and backgrounds. For the training of the database, an iterative method has been started to load an image and preprocess the images one by one to create the images with same orientation and other properties. If the images are in greyscale then they would be concatenated to create three dimension image. For the efficiency the images are resized so that the normalization can be achieved. Transfer learning is the type of deep learning applications is called transfer learning in which a predefined and pretrained model or the network can be redefined and fine-tuned for the personal use or the customized data to be trained on the model by modifying some of the layers. A new pretrained network can be utilized to train and learn from a new job. Transfer and finetune a trained network is easier than starting from scratch [24]. The features and other weights learnt by model is easier to transfer with lower number of images [26]. Here we used a pretrained alexnet and single class support vector machine to train on the new dataset containing four hundred different images. The network has been fine-tuned, trained and the predictability has been assessed for the accuracy of the model with the machinery element. The final stage of our experiment was the deployment of the result and the performance measurement of the model.

III. RESULTS AND DISCUSSION

For the testing of the data, the new images are to be loaded by the program. The images are automatically labelled and stored on a disk. The benefit of the loading of the data is to adopt many more images to be added in the directory and the network can be retrained without any hassle. The system then bifurcates the 320 images as training images and the 80 images for the testing purposes or the validation purpose. The pretrained network is loaded and finetuned to recognize the abnormal ones. The images are then displayed and classified with the other ones. The images are classified with the help of validation images through the fine-tuned network. Some of the images are displayed from the validation images with the predicted labels. The final stage of the classification accuracy to be presented from the validation set. The system generated accuracy of more than 98% of accuracy by classifying 392 images correctly and showing a total of eight images as abnormal images and called them as anomaly detection.

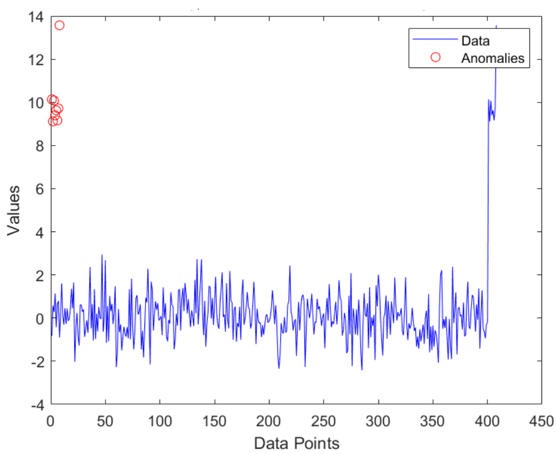

Figure 5 : Anomally detection

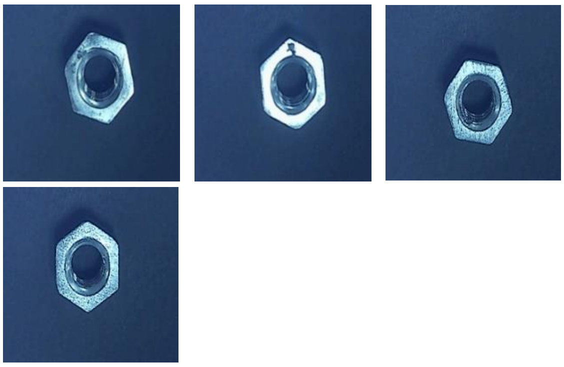

Figure 6: Anomally detection showing sample objects in single color

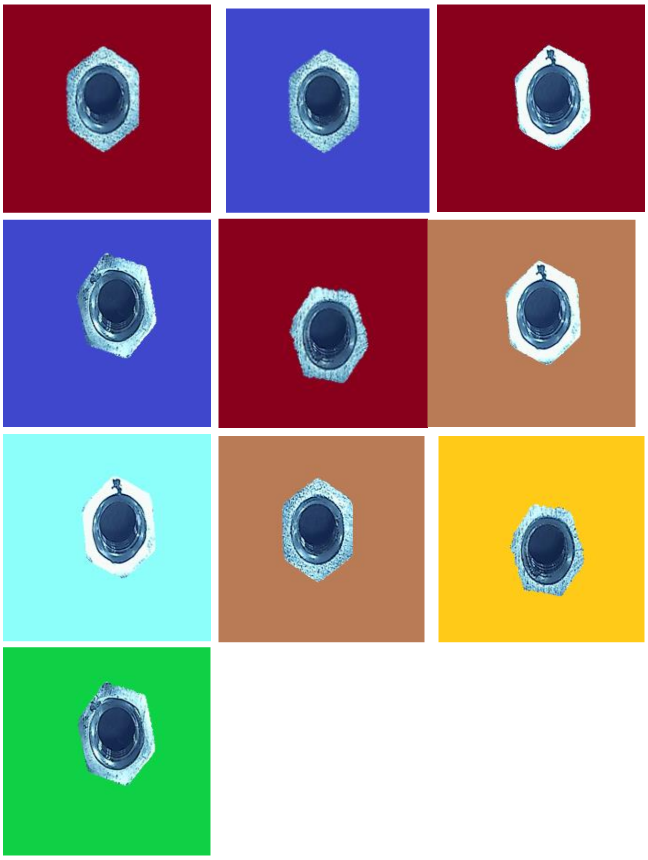

Figure 7: Anomally detection showing sample objects in varying color

IV. CONCLUSION

Detection of the objects with differentiating properties from a big set of data is called anomaly detection. With the advent of machine learning, anomaly detection has been a topic of interest for the researchers to make machine learn to identify the object (s) which does not fit within a particular class or group of objects. Along with many of its applications, anomaly detection in industrial image has been a direction of the research. The current study has presented the anomaly detection of machinery elements among the set of four hundred images of the dataset under experiment. The training model has used bidirectional LSTM which gets a feature vector of twelve features, selected and extracted with already defined algorithm. The model has been trained on 400 of images by labelling them manually. The system has achieved an accuracy of the 98% which can be increased by adding more images to data with exhaustive learning algorithms. The current research has many directions for the future including experimenting more and more machinery elements, adding more data and performing experiments with other classification and learning algorithms.

V. REFERENCES

[1]. V. Chandola, A. Banerjee, V. Kumar, Anomaly detection: A survey, ACM Computing Surveys (CSUR) 41 (2009) 1–58.

[2]. Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, Gradient-based learning applied to document recognition, Proceedings of the IEEE 86 (1998) 2278–2324.

[3]. A. Graves, Generating sequences with recurrent neural networks, arXiv preprint arXiv:1308.0850, 2013.

[4]. G.E. Hinton, A. Krizhevsky, S.D. Wang, Transforming auto-encoders, in: International conference on artificial neural networks, Springer, 2011, pp. 44–51..

[5]. I.J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio, Generative adversarial nets, in: Proceedings of the 27th International Conference on Neural Information Processing Systems- Volume 2, MIT Press, 2014, pp. 2672–2680.

[6]. K. Oksuz, B.C. Cam, S. Kalkan, E. Akbas, Imbalance problems in object detection: A review, IEEE Transactions on Pattern Analysis and Machine Intelligence (2020).

[7]. Xueyuan Duan, Yu Fu, Kun Wang, Network traffic anomaly detection method based on multi-scale residual classifier, Computer Communications, Volume 198, 2023,Pages 206-216, ISSN 0140-3664, https://doi.org/10.1016/j.comcom.2022.10.024.

[8]. Ruikang Liu, Weiming Liu, Mengfei Duan, Wei Xie, Yuan Dai, Xianzhe Liao, MemFormer: A memory based unified model for anomaly detection on metro railway tracks,Expert Systems with Applications,Volume 237, Part B,2024,121509,ISSN 0957-4174,https://doi.org/10.1016/j.eswa.2023.121509.

[9]. Bekhzod Alisher ugli Olimov, Kalyana C. Veluvolu, Anand Paul, Jeonghong Kim, UzADL: Anomaly detection and localization using graph Laplacian matrix-based unsupervised learning method,Computers & Industrial Engineering,Volume 171,2022,108313,ISSN 0360-8352,https://doi.org/10.1016/j.cie.2022.108313.

[10]. T.W. Cenggoro, Deep learning for imbalance data classification using class expert generative adversarial network, Procedia Computer Science 135 (2018) 60–67.

[11]. S. Bulusu, B. Kailkhura, B. Li, P.K. Varshney, D. Song, Anomalous example detection in deep learning: A survey, IEEE Access 8 (2020) 132330–132347.

[12]. R. Chalapathy, S. Chawla, Deep learning for anomaly detection: A survey, arXiv preprint arXiv:1901.03407, 2019.

[13]. G. Pang, C. Shen, L. Cao, A.V.D. Hengel, Deep learning for anomaly detection: A review, ACM Computing Surveys (CSUR) 54 (2021) 1–38.

[14]. F. Di Mattia, P. Galeone, M. De Simoni, E. Ghelfi, A survey on gans for anomaly detection, 2019, arXiv preprint arXiv:1906.11632.

[15]. V. Chandola, A. Banerjee, V. Kumar, Outlier detection: A survey, ACM Computing Surveys (CSUR) 14 (2007) 15.

[16]. E. Zisselman, A. Tamar, Deep residual flow for out of distribution detection, in, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 13994–14003.

[17]. M.A. Pimentel, D.A. Clifton, L. Clifton, L. Tarassenko, A review of novelty detection, Signal Processing 99 (2014) 215–249.

[18]. A. Ayadi, O. Ghorbel, A.M. Obeid, M. Abid, Outlier detection approaches for wireless sensor networks: Asurvey,ComputerNetworks129(2017)319–333.

[19]. C.C. Aggarwal, An Introduction to Outlier Analysis, Springer, 2017, pp. 1–34.

[20]. M. Goldstein, S. Uchida, A comparative evaluation of unsupervised anomaly detection algorithms for multivariate data, PloS One 11 (2016) e0152173.

[21]. L. Ruff, J.R. Kauffmann, R.A. Vandermeulen, G. Montavon, W. Samek, M. Kloft, T.G. Dietterich, K.-R. Müller, A unifying review of deep and shallow anomaly detection, Proceedings of the IEEE (2021).

[22]. A. Taha, A.S. Hadi, Anomaly detection methods for categorical data: A review, ACM Computing Surveys (CSUR) 52 (2019) 1–35.

[23]. H. Wang, M.J. Bah, M. Hammad, Progress in outlier detection techniques: A survey, IEEE Access 7 (2019) 107964–108000.

[24]. R. Foorthuis, On the nature and types of anomalies: A review of deviations in data, 2020, arXiv preprint arXiv:2007.15634.

[25]. A. Boukerche, L. Zheng, O. Alfandi, Outlier detection: Methods, models, and classification, ACM Computing Surveys (CSUR) 53 (2020) 1–37.

[26]. D. Miljkovic´, Review of novelty detection methods, in: The 33rd International Convention MIPRO, IEEE, 2010, pp. 593–598..

[27]. A. Carreño, I. Inza, J.A. Lozano, Analyzing rare event, anomaly, novelty and outlier detection terms under the supervised classification framework, Artificial Intelligence Review 53 (2020) 3575–3594.