General

ID[1]		
Use case name	Anomaly Detection in Sensor Data Using Deep Learning techniques	
Application domain	Maintenance & support	
Deployment model	Hybrid or other (Cloud or on premise deployment)	
Status	PoC	
Scope[2]	Temporal Data captured from sensors	
Objective(s)	Identify Anomalies and Events by learning the temporal patterns of sensor data, based on Deep Learning techniques.	
Narrative	Short description (not more than 150 words)	Mechanical devices such as engines, vehicles, aircrafts, etc., are typically instrumented with numerous sensors to capture the behaviour and health of the machine. The sensors temporal data has several complex patterns that are very hard to identify with traditional methods. We have proposed the use of Deep Learning algorithms for analysing such temporal patterns for anomaly/event detection, diagnosis, root cause analysis. Algorithms proposed so far are LSTM-AD, EncDec-AD, online RNN-AD. We used industrial datasets wherever possible and publically available datasets in other scenarios. In most of the cases, our algorithms were significantly better than other methods.
	Complete description	Mechanical devices such as engines, vehicles, aircrafts, etc., are typically instrumented with numerous sensors to capture the behaviour and health of the machine. However, there are often external factors or variables which are not captured by sensors leading to time-series which are inherently unpredictable. For instance, manual controls and/or unmonitored environmental conditions or load may lead to inherently unpredictable time-series. Detecting anomalies/events in such scenarios becomes challenging using standard approaches based on mathematical models that rely on stationarity, or prediction models that utilize prediction errors to detect anomalies. LSTM-AD Our Work started with Stacked LSTM network which is trained on non-anomalous data and used as a predictor over a number of time steps. The resulting prediction errors are modeled as a multivariate Gaussian distribution, which is used to assess the likelihood of anomalous behavior. The efficacy of this approach was demonstrated on four datasets: ECG, space shuttle, power demand, and multi-sensor engine dataset. EncDec-AD As an extension to the prior work we proposed a Long Short Term Memory Networks based Encoder-Decoder scheme for Anomaly Detection (EncDec-AD) that learns to reconstruct normal time-series behavior, and thereafter uses reconstruction error to detect anomalies. We experimented with three publicly available quasi predictable time-series datasets: power demand, space shuttle, and ECG, and two real-world engine datasets with both predictive and unpredictable behavior. We had shown that EncDec-AD is robust and can detect anomalies from predictable, unpredictable, periodic, aperiodic, and quasi-

		periodic time-series. Further, we showed that EncDec-AD is able to detect anomalies from short time-series (length as small as 30) as well as long time-series (length as large as 500). Online-AD The common approach of training one model in an offline manner using historical data is likely to fail under dynamically changing and non-stationary environments where the definition of normal behavior changes over time making the model irrelevant and ineffective. We described a temporal model based on Recurrent Neural Networks (RNNs) for time series anomaly detection to address challenges posed by sudden or regular changes in normal behaviour. The model is trained incrementally as new data becomes available, and is capable of adapting to the changes in the data distribution. RNN is used to make multi-step predictions of the time series, and the prediction errors are used to update the RNN model as well as detect anomalies and change points. Large prediction error is used to indicate anomalous behaviour or a change (drift) in normal behaviour. Further, the prediction errors are also used to update the RNN model in such a way that short term anomalies or outliers do not lead to a drastic change in the model parameters whereas high prediction errors over a period of time lead to significant updates in the model parameters such that the model rapidly adapts to the new norm. We demonstrate the efficacy of the proposed approach on a diverse set of synthetic, publicly available and proprietary real-world datasets.		
Stakeholders[3]	Maintenance and support functions, Monitoring, Procurement			
Stakeholders' assets, values[4]				
System's threats and vulnerabilities[5]	• Data biases could result in high number of false negatives and false positives that could result in heavy losses. • Accuracy cannot be 100%.			
Key performance indicators (KPIs)	ID	Name	Description	Reference to mentioned use case objectives
	1	Precision	Correctly Predicted Anomalous scenarios/ Total Anomalous scenarios predicted	
	2	Recall	Correctly Predicted Anomalous scenarios /Total Anomalous Scenarios	
AI features	Task(s)	Prediction		
	Method(s)[6]	Deep Learning		
	Hardware[7]			
	Topology[8]			
	Terms and concepts used[9]	Deep Learning, LSTM, encoder-decoder, Temporal data		
Standardization opportunities/ requirements	• Sensor data collection			

Challenges and issues	• Noisy Data • Data with missing temporal features • Rarity of Anomalous Data	
Societal concerns	Description	
	SDGs[10]	Industry, Innovation, and Infrastructure

Data (optional)

Data characteristics	
Description	Multiple datasets(publically available, real industrial) were used
Source[11]	
Type[12]	Temporal data
Volume (size)	
Velocity (e.g. real time)[13]	
Variety (multiple datasets)[14]	Space shuttle, ECG, Engine, Power demand
Variability (rate of change)[15]	
Quality[16]	

Process scenario (optional)

Scenario conditions					
No.	Scenario name	Scenario description	Triggering event	Pre-condition[17]	Post-condition[18]

Training (optional)

Scenario name	Training				
Step No.	Event[19]	Name of process/Activity[20]	Primary actor	Description of process/activity	Requirement

Specification of training data[21]	

Evaluation (optional)

Scenario name	Evaluation				
Step No.	Event[22]	Name of process/Activity[23]	Primary actor	Description of process/activity	Requirement

Input of evaluation[24]	
Output of evaluation[25]	

Execution (optional)

Scenario name	Execution				
Step No.	Event[26]	Name of process/Activity[27]	Primary actor	Description of process/activity	Requirement

Input of Execution[28]	
Output of Execution[29]	

Retraining (optional)

Scenario name	Retraining				
Step No.	Event[30]	Name of process/Activity[31]	Primary actor	Description of process/activity	Requirement

Specification of retraining data[32]	

References

References						
No.	Type	Reference	Status	Impact on use case	Originator/organization	Link

1. Pankaj Malhotra, Anusha Ramakrishnan, Gaurangi Anand, Lovekesh Vig, Puneet Agarwal, Gautam Shroff, LSTM-based Encoder-Decoder for Multi-sensor Anomaly Detection, https://arxiv.org/abs/1607.00148
2. Sakti Saurav, Pankaj Malhotra, Vishnu TV, Narendhar Gugulothu, Lovekesh Vig, Puneet Agarwal, Gautam Shroff, Online anomaly detection with concept drift adaptation using recurrent neural networks, CoDS-COMAD '18, Proceedings of the ACM India Joint International Conference on Data Science and Management of Data, Goa, India — January 11 - 13, 2018

Footnote

[1] Leave this cell blank.

[2] The scope defines the limits of the use case.

[3] Stakeholder involved in the scenario - examples are: type of organization; customers, 3rd parties; end users; humans; environment; negative stakeholders (attackers, criminals, etc).

[4] Assets and values that are valuable to the stakeholders and at the risk of being compromised by the AI system deployment – examples can include competitiveness; reputation or trust; fairness; safety; privacy; stability; etc.

[5] Threats and vulnerabilities can compromise the assets and values above. Examples are: different sources of bias; incorrect AI system use; new security threats; challenges to accountability; new privacy threats (hidden patterns).

[6] AI method(s)/framework(s) used.

[7] Hardware system used.

[8] Topology is the study of geometric forms differentiated by intersection and bifurcation. The term is used for the graphic aspects network architectures.

[9] Terms and concepts listed here can be used to extend the work of WG 1 (AWI 22989 and AWI 23053) as necessary.

[10] The Sustainable Development Goals (SDGs), otherwise known as the Global Goals, are a collection of 17 global goals set by the United Nations General Assembly. SDGs are a universal call to action to end poverty, protect the planet and ensure that all people enjoy peace and prosperity.
See URL for more details: http://www.undp.org/content/undp/en/home/sustainable-development-goals.html

[11] Origin of data, which could be from instruments, IoT, web, surveys, commercial activity, or from simulations.

[12] Structured/unstructured Images, voices, text, gene sequences, and numerical. Composite: time-series, graph-structured

[13] The rate of flow at which the data is created, stored, analysed, or visualized.

[14] Data from a number of domains and a number of data types. The wider range of data formats, logical models, timescales, and semantics complicates the integration of the variety of data.

[15] Changes in data rate, format/structure, semantics, and/or quality.

[16] Completeness and accuracy of the data with respect to semantic content as well as syntactical of the data (such as presence of missing fields or incorrect values)

[17] Describe which condition(s) should have been met before this scenario happens.

[18] Describe which condition(s) should prevail after this scenario happens. The post-condition may also define "success" or "failure" conditions.

[19] The event that triggers the step. This might be completion of the previous event.

[20] Action verbs should be used when naming activity.

[21] Training data can be further specified.

[22] The event that triggers the step. This might be completion of the previous event.

[23] Action verbs should be used when naming activity.

[24] Specify input of evaluation.

[25] Specify output of evaluation.

[26] The event that triggers the step. This might be completion of the previous event.

[27] Action verbs should be used when naming activity.

[28] Specify input of evaluation.

[29] Specify output of evaluation.

[30] The event that triggers the step. This might be completion of the previous event.

[31] Action verbs should be used when naming activity.

[32] Retraining data can be further specified.