

Name: Jorge Blanco  
Student Id: 24246948  
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Assignment 2

## **1 Background**

This literature review aims to explore the current research on AI vision, especially the detection of abrupt anomaly using data streams as input. The objective is to apply the findings to a complex construction site workflow as a new system.

### **1.2 Context**

Managing a construction project is highly complex because of the number of third-party vendors involved and the safety regulations. However, the number one headache is allocating resources, who can be independent contractors themselves, and who, once booked, will get paid regardless of whether they have performed the task they got booked for. Because of the dynamic nature of construction sites, things can change quickly, and in some cases, resources stand idle, which leads to financial loss. Repeat the same mistake more than once over the lifecycle of a project, and the economic loss could be substantial.

### **1.3 Tool pre-installation walk**

A key concept of this phase is that tools are delivered as a unit, and if a tool is damaged, the repair process is not that simple, and in some cases, the tool itself is costly. To avoid surprises, several human resources are pulled in for a tool pre-installation walk to ensure the transition from the delivery bay to the final resting place goes smoothly and potential issues are flagged and fixed before the delivery date. Another interesting thing to remember is that a construction site does not come to a standstill for a tool pre-installation walk, and managing resources in an already congested area becomes highly critical.

### **1.4 Proposed solution**

The proposed workflow aims to perform the tool pre-installation walk using an unsupervised rover with a camera to capture all the information usually captured by the numerous human resources pulled in for the walk and speed up the turnaround period for identified issues. Because of the restrictive nature of complex construction sites, the proposed solution will be evaluated in a simulated physical controlled environment.

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## **2 Related Work**

### **2.1 Nature of data-streams**

Data streams tend to generate a lot of data, and decisions need to be made in real time. Storing data streams to train a model is not a practical solution, unlike batch learning, where stored data is used to train the model.

#### **2.1.1 Lack of labels**

With the volume of data generated by data streams, it is not always possible to have labels in advance, as observations do not always follow a learned pattern (Jakubowski et al., 2024).

#### **2.1.2 ML model expectations**

Data should only be processed once. The model should adapt to new data but remember old observations (Jakubowski et al., 2024).

#### **2.1.3 Imbalanced data**

Because an anomaly constitutes a fraction of the data, it makes the data imbalanced, leading to a biased model (Jakubowski et al., 2024).

#### **2.1.4 Deviation of the environment**

There are circumstances where a deviation from the environment triggers the anomaly alert. Industrial sites that are in the open air are exposed to this phenomenon because of the weather (Jakubowski et al., 2024).

## **2.2 Drift problem**

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Because of the dynamic nature of data streams, the only way to detect an anomaly is for the drift problem to manifest itself, which can occur gradually, abruptly, incrementally, recurrently, or temporarily (Aydogdu et al., 2020).

### **2.3 Limitations of deep learning**

Deep learning-based pattern recognition depends on the training set and requires a lot of computational power just to bring the model online or for retraining (Sultani et al. 2018, Chu et al. 2018, Tang et al. 2020, ...). In real-time environments, that is not practical, as events are dynamic, and retraining the model each time to a new anomaly is impractical.

### **2.4 Temporal segments**

The size of the temporal segment will have to be tuned in like a hyperparameter: ideally, the proposed solution should adapt the segment length based on the observations. Several papers (Zhou et al., 2023) use deep learning, which is not perfect for real-time environments.

### **2.5 Unsupervised anomaly detection algorithms**

Many research papers have focused on a single hidden-layer feedforward neural network to overcome the limitations of deep learning networks.

#### **2.5.1 ELM**

It is a single hidden-layer feedforward neural network that has been successfully applied in many real-time learning tasks for classification (Wang et al., 2021), making it the foundational block for many algorithms. However, it can't handle sequential learning, and assigning random weights to input layers makes it inconsistent.

#### **2.5.2 OS-ELM**

It is a state-of-the-art data stream classification algorithm that can handle online sequential learning (Liang et al., 2006) but cannot handle abrupt changes.

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### **2.5.3 UFROS-ELM**

It is an unsupervised feature representation (Aydogdu et al., 2020) that modifies OS-ELM with ELM-AE (ELM autoencoder) and works well with dynamic data streams, where the characteristics of the data change overtime.

## **2.6 Model instances**

With single model instances, there is a risk of pattern forgetting. To overcome this problem, several online models are spun up, and the group votes on the final classification result, with out-of-date models being retrained offline (Jakubowski et al., 2024).

## **2.7 False positives**

Because anomaly events are rare and dispersed, the probability of generating a false positive is high since the system spends most of its time dealing with positive events.

### **2.7.1 MIL**

It is a weakly labelling technique (Carbonneau et al., 2018) that looks at the entire image and not at the items in it. However, it fails to adapt at the bag level for dynamic events.

#### **2.7.1 Mil with progressive learning**

By incorporating progressive learning (Aydogdu et al., 2024), the technique can adapt and not forget previous observations, as that is a constant issue with online models (forgetting past observations with each retraining).

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