D2.4 – Detailed description of the safety functionalities and worker notifications

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Abstract

This is the first version of Deliverable 2.4 "Detailed description of the safety functionalities and worker notifications" in BIMprove project. It will be updated at M20. This deliverable describes the automatic detection of safety risk factors from photographs at a construction site and the management of safety risk data and worker notifications. The focus is in covering fall and fire risks.

Keywords

Safety, Risk, Object detection

Revisions

Version	Submission date	Comments	Author
v0.1	30th June 2021	Initial version	Anu Purhonen (VTT), Tommi Aihkisalo (VTT), Ilkka Niskanen (VTT)
v0.2	16th August 2021	Submitted for internal review	Anu Purhonen (VTT), Tommi Aihkisalo (VTT), Ilkka Niskanen (VTT)
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V1.0	31st August 2021	Approved, final version	Andrej Cibicik (SINTEF)

Disclaimer

Acronyms and definitions

Acronym	Meaning
AI	Artificial Intelligence
API	Application Programming Interface
BIM	Building Information Modelling
GPU	Graphics Processing Unit
H&S	Health & Safety
JSON	JavaScript Object Notation
ML	Machine Learning
REST	Representational State Transfer

BIMprove project

In the past 20 years, productivity in the European construction industry has increased by 1% annually only, which is at the lower end compared to other industrial sectors. Consequently, the sector has to step up its digitization efforts significantly, on the one hand to increase its competitiveness and on the other hand to get rid of its image as dirty, dangerous and physical demanding working environment. Construction industry clearly needs to progress beyond Building Information Modelling when it comes to digitizing their processes in such a way that all stakeholders involved in the construction process can be involved.

The true potential of comprehensive digitization in construction can only be exploited if the current status of the construction work is digitally integrated in a common workflow. A Digital Twin provides construction companies with real-time data on the development of their assets, devices and products during creation and also enables predictions on workforce, material and costs.

BIMprove facilitates such a comprehensive end-to-end digital thread using autonomous tracking systems to continuously identify deviations and update the Digital Twin accordingly. In addition, locations of construction site personnel are tracked anonymously, so that **BIMprove** system services are able to optimize the allocation of resources, the flow of people and the safety of the employees. Information will be easily accessible for all user groups by providing personalized interfaces, such as wearable devices for alerts or VR visualizations for site managers. **BIMprove** is a cloud-based service-oriented system that has a multi-layered structure and enables extensions to be added at any time.

The main goals of **BIMprove** are a significant reduction in costs, better use of resources and fewer accidents on construction sites. By providing a complete digital workflow, BIMprove will help to sustainably improve the productivity and image of the European construction industry.

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1. Introduction

Purpose of this document is to describe the BIMprove functionalities that are specific to support safety at the construction sites. The rate of work accidents in the construction domain is high. Safety risk for an individual worker depends on many risk factors including occupation type (e.g. a roofer vs a concrete worker), activity type (e.g. variation in used tools), temporal and spatial factors (e.g. work duration or concurrent activities), and used safety management controls (e.g. safety planning, training, and use of protection systems) (Choe & Leite 2020). Recently, there have been steps to digitalise health and safety (H&S) management. For example, there have been developed approaches for safety planning at design phase with integrating safety objects to BIM (Cortés-Pérez et al. 2020; Getuli et al. 2017), for automating H&S inspections (Kolar et al. 2018; Fang, Li, et al. 2018; Fang, Ding, et al. 2018), and hazard assessment (Amiri et al. 2017). There are also commercial tools for supporting H&S at construction sites. The aim of the functionalities described here is to mitigate safety risks by monitoring the safety status at a construction site and notifying workers of potential safety risks supplementing the previous and existing developments and functionalities. Especially, the focus here is in protecting workers from falling from heights and in detecting fire hazards.

The risk of falling can be mitigated by using fall protection systems. (OSHA 2015) classifies conventional fall protection systems into guardrail systems, safety nets, and personal fall arrest systems. Other fall protection systems include positioning devices that allow working with both hands free while on an elevated vertical surface and fall restraint systems that do now allow fall of any distance. Additional fall protection can be provided with warning lines on a roof to visually indicate unprotected and avoidable areas, using controlled access zones, and with safety monitoring systems that a designated person uses to monitor workers and to warn them when they are close to a fall hazard.

According to BIMprove deliverable 1.8, the most frequent fire related scenarios include untidy construction sites, heat sources or electricity related not supervised, potentially dangerous tasks, managing negligence, untrained personnel, incorrect material warehousing, blocked emergency exits, and adjoining buildings or structures.

This deliverable will have two releases. This first release focuses on functionalities related to automating some of the safety inspections and construction of the risk data management. More specifically, this release describes how safety barriers, safety nets and untidy places with potential fire risk can be automatically detected at the construction sites. The second release at M20 will finalise the description of the functionalities and interfaces to the other functionalities of BIMprove.

Relationships to other deliverables in BIMprove project:

- The functionalities are based on the requirements defined in D1.8 Risk and safety assessment methods
- External interfaces are defined in D1.5 Data Integration Interfaces for Building Industry using BIM and Digital Building Twins

The conceptual model of safety risk management is presented in Figure 1.

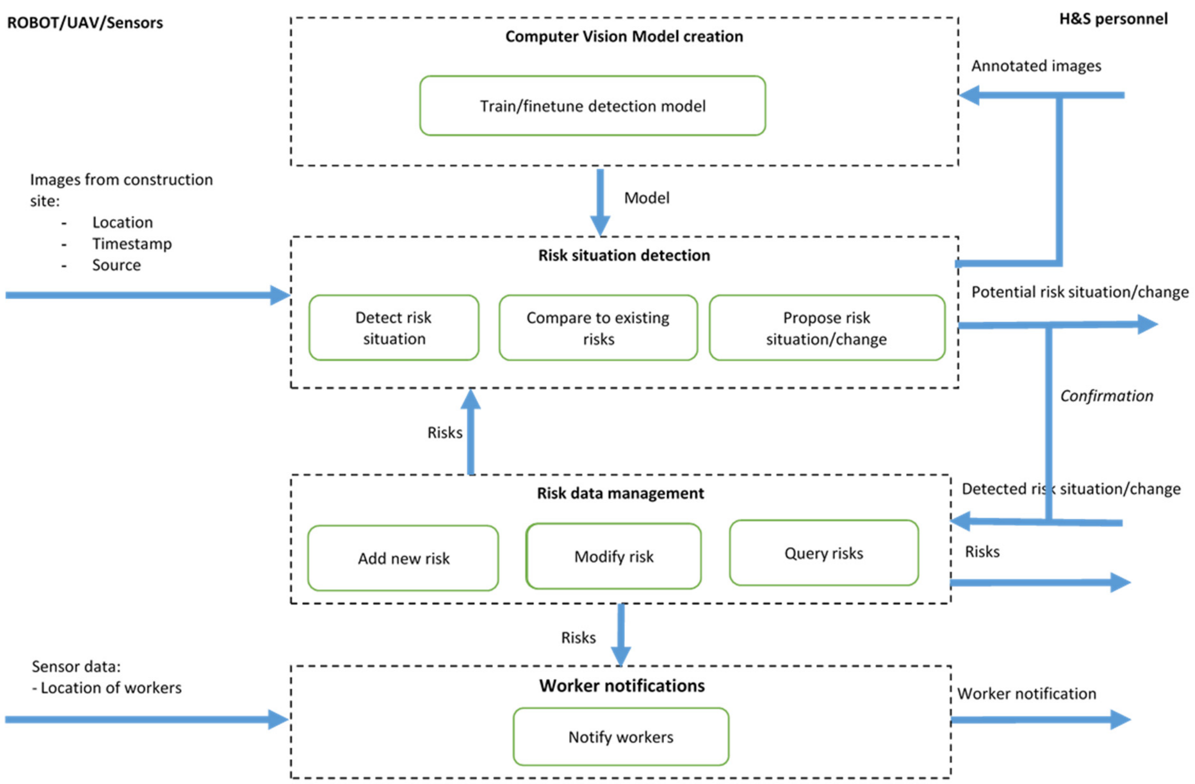

Figure 1 Conceptual model

The conceptual model presents an initial idea how different components in safety risk management would work together. The safety risk management is divided into four modules. The intent of Computer Vision Model Creation (in this first phase) is to train a model for visually detecting safety barriers, safety nets, and untidy places i.e. garbage from pictures taken at construction sites. A set of annotated images is required as training data for such model. The intent of the Risk Situation Detection module is to use the created model to analyse images taken at construction sites. In case a potential risk situation is found, then it is first clarified whether that is a new finding or is it already in the risk database. Potential new risks or changes in risk situation are also confirmed by H&S workers before adding them to the database. Risk Data Management module contains a risk database where the risk information is stored. Finally, the purpose of Worker Notification module is to use the risk information and potential sensor data to alert workers of risk situations. The implementation of each module is elaborated in the following chapters.

2. Computer Vision Model Creation

The automated detection of safety factors and risks is based on detecting from the visual material the conditions and situations which may contribute to formation of a risk. The digital visual material, photographs or video, collected from the work site may be analysed to detect the potential risks and related factors with a suitable deep learning based computer vision solution. Before reaching such capability, a model based on the deep neural networks needs to be trained as in any other data based machine learning solutions using a suitable training data set. For the deep learning purposes, the training data needs to be gathered, stored, quality controlled and annotated with suitable labels.

The machine learning based computer vision model is trained for detecting risks or risk countermeasures at the construction sites. In general, this requires substantial amounts of training data in a form of digital images and/or video containing such features as wished to be detected. The quality of the images is important in two senses. Firstly, semantically they should contain what is desired to be detected and secondly technical quality should be reasonable regarding resolutions etc. The resolution usually may have an impact on the final detection precision but for training and detection they are always practically scaled down to a fixed size as dictated by the detection algorithm. However, if the final detection system should be robust and able to detect even in less than perfect conditions some, even manmade, imperfections are desired in the training data. The raw digital material as such is not enough to reach the adequate levels of detection precision in the final model within a reasonable computing time. Thus, the training data needs to be refined manually with an annotation process that should highlight those risk objects on the images as identified in the corresponding risk model. Especially in this case annotation classes will include safety barriers and safety nets as risk countermeasures; and piles of garbage as a fire risk factor with locating and labelling bounding boxes as in the Figure 2 and Figure 3 original and annotated image respectively. Sample images in this document are provided by the courtesy of HRS possessing all rights to the original images.

Figure 2 Original raw image from the construction site. (Copyright HRS)

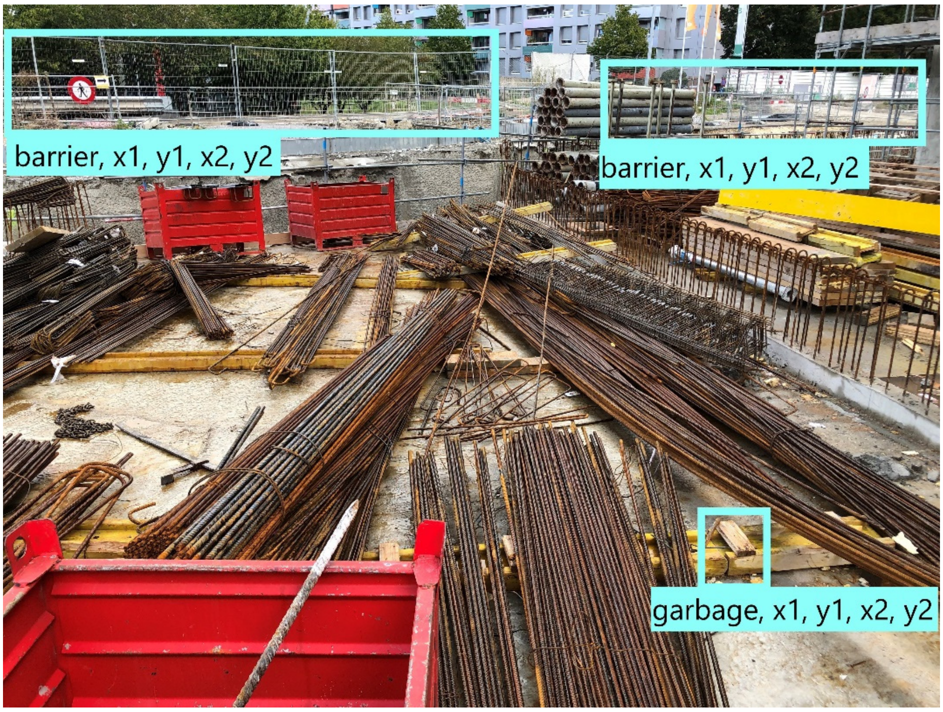

Figure 3 Labelled and annotated image from the construction site. Annotation here contains barrier and garbage labels with bounding boxes and their x and y coordinates for illustrative purposes only. (Copyright HRS)

The annotation process produces training data capturing samples of the needed classes with a class label including the location of the item with a bounding box. The boxes' location on the original image's coordinate space consists of x, y coordinates of the upper left, and lower right corners for each labelled instance. The detection system when operational will be able to detect and predict these same attributes from the construction site images for further usage in risk analysis. The annotation and the output of detection system will, thus, contain the following:

Class – object class: barrier | net | garbage

x1 – upper left corner x-coordinate of the bounding box

y1 – upper left corner y-coordinate of the bounding box

x2 – lower right corner x-coordinate of the bounding box

y2 – lower right corner y-coordinate of the bounding box

Many of the freely available tools will be applicable for the annotation work and produce suitable annotations for the training data.

The iterative model creation process may include several training and verifying cycles. In each cycle we try to find suitable model architecture and its neural network training and hyperparameters to improve the overall detection precision. The current trend in the visual object detection and image classification is towards the deep convolutional neural networks. These outlay a challenge on the available data quantities and quality but also on the available computing resources. This usually means GPU resources very beneficial for parallel floating point operations evidential in ML processes. To maintain a reasonable time frame in the training process finetuning pre-existing models and transfer learning procedure should be favoured. The finetuning and transfer learning utilizes an existing model to diversify it to detect new classes of objects in the new domain. The results of the training cycles may also suggest deficiencies in the data and corrective requirements may be communicated to the training data gathering and creation processes that are, however, outside of this context. Should the training be successful, in the end the system should be able to produce detections following the same scheme as in the training data described earlier, which includes the object label and its approximate location on the provided image.

In the object detection application domain various models based on the convolutional networks have proved to be suitable and precise enough. Solutions like Faster R-CNN (Ren 2017) and various versions of Yolo (Redmon 2018) has evidentially been highly performing even with video feeds while maintaining adequate detection precision. Figure 4 represents ResNet-101 (He 2016) solution for object classification and localization architecture.

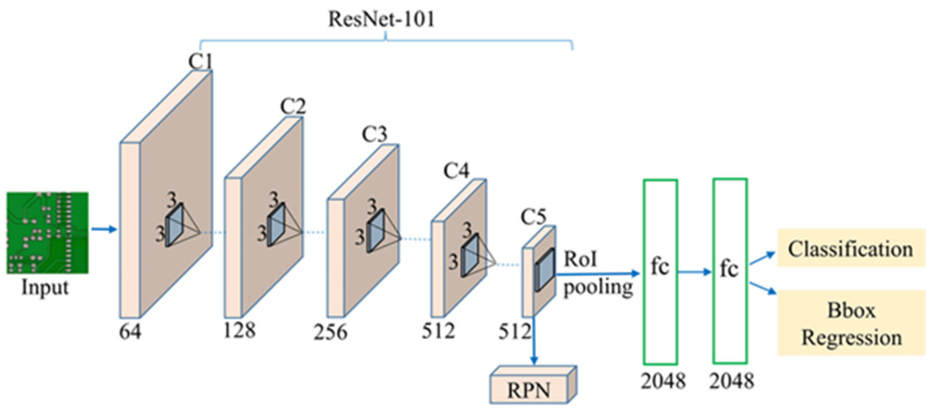

Figure 4 Convolutional network based ResNet with convolutional layers C1-C5 consisting of 64, 128, 256, 512 and 512 internal layers respectively completed with two fully connected (fc) layers of size 2048 neurons responsible for output of detected object classification and bounding box dimensions.. Image source (Ding 2019).

As the current tendency is towards the even deeper and more complex machine learning model architectures, we cannot ignore the performance costs of such solutions. It may be desirable if the created model would maintain high level of precision in detection but also allow detection processing on the handheld devices with a live video streaming material also as many handheld devices possess substantial amounts of graphic displaying but also AI targeted GPU processing power. Initially, however, the detection is intended to be provided as a server based service contributing visual analysis results for the knowledge based final risk analysis processes as described later.

3. Risk Situation Detection

The purpose of risk situation detection is to support the work of H&S personnel in detecting either new risk situations or updating the status of an earlier found risk. The first version that is presented in this deliverable focuses on detecting safety barriers, safety nets, and untidy places in images taken at the construction site. The images are taken by robots, drones, or construction workers at the construction site. The location of the scene the image has been taken of should be mapped to the BIMprove coordinate system. The actual process for this is to be defined.

The visual potential safety factor and risk detection is done by using the available image or video data from the construction site. The visual material is assessed with the computer vision solution for which a deep learning based model was created earlier. The arriving digital material submitted for the analysis needs a storage solution before the visual risk detection will take place. The results and the potential findings from the visual material are subsequently submitted to the risk database for further integration and analysis with the existing knowledge. The results data may include among other data also the analysed image with the detected and highlighted risk objects for human verification and viewing.

4. Risk Data Management

Risk data management includes i) using a common vocabulary and taxonomy for defining the main concepts and relationships between concepts, ii) storing risk related data into a graph database, the database is structured based on the defined risk taxonomy and iii) assessing discovered risks and notifying workers on possible threats. In this chapter, the required elements for the comprehensive risk management approach are described in more detail.

4.1. Risk ontology

A current trend in the construction industry is that the work is more often done by multidisciplinary and geographically dispersed teams. However, members of distributed teams may have difficulty establishing a shared context (Pallot 2011). The absence of shared context impedes the reaching of mutual understanding, which may significantly impact collaboration effectiveness and efficiency (Pallot et al. 2010; Clark and Brennan, 1991). An increasingly utilized method to facilitate common understanding between members of a collaborative team is the use ontologies. By definition, ontology is an explicit and formal specification of a conceptualisation of a domain of interest (Gruber 1993). Furthermore, ontology is defined as a controlled vocabulary that describes objects and the relations between them in a formal way (Berners-Lee et al. 2001). Finally, ontologies, provide effective machine-to-machine communication capabilities enabling computational entities and services to have a common set of concepts and vocabularies for representing knowledge about a domain of interest (Wang et al. 2002).

In BIMProve, all data related to safety risks is modelled with a specific risk data management ontology. The ontology aims at formally representing risk-specific concepts and their relationships, and metadata that enables the system to better understand and reason about the structure and purpose of the data. Moreover, it constitutes a common data representation for the heterogeneous group of stakeholders participating in the safety risk management on the construction site. The resulting risk ontology will be developed iteratively, which means that it evolves during the course of this project as the requirements for the information model become more and more mature and specific. The first version of the risk ontology is represented in the Figure 5. As can be seen, some class definitions of the ontology are still incomplete. Hence, for example the class "RiskZone" contains no properties at this stage.

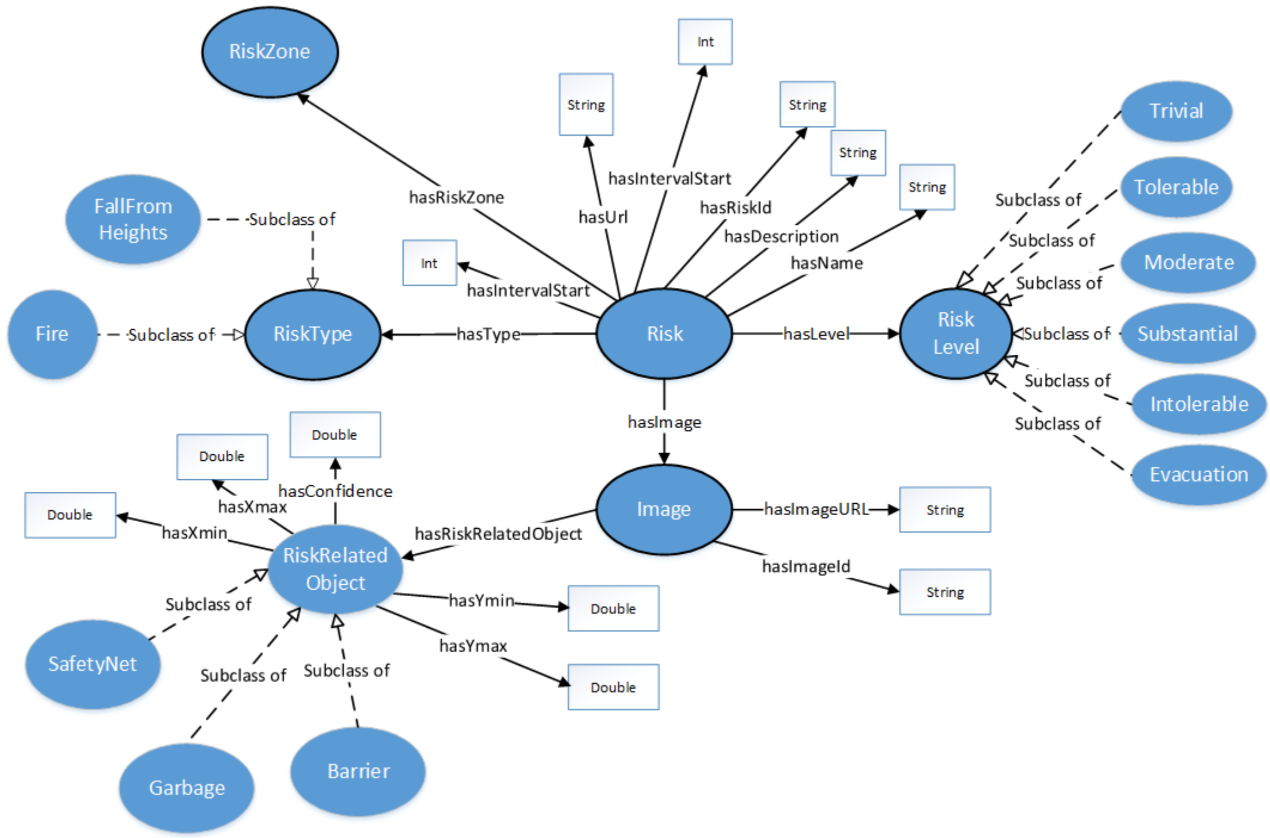

Figure 5 First version of the risk ontology

The first version of the risk ontology is defined based on the concepts and terms that are currently identified in BIMProve as essential for risk management. The central class in the ontology is Risk that has certain data properties such as name and description. In addition, the Risk class is associated with a risk level that is divided into several subclasses representing different risk levels. The class Risk can also be linked with different risk types (i.e. fire and fall from heights) and risk zones. In addition, instances of the class Risk can also have images that represent characteristics of a risk.

The objective of the class Image is to capture the knowledge extracted from pictures taken from a construction site. It holds two data properties that are URL (pointing to the storage location of the image) and ID of the image. The Image class is associated with the RiskRelatedObject class that models the concepts that are essential for the above described "Automated Detection of Safety Factors and Risks" service. In more detail, the class defines the information that can be automatically detected from the pictures by the utilized deep learning based computer vision solution. The RiskRelatedObject class has three subclasses that are SafetyNet, Garbage and Barrier. These subclasses represents concrete physical objects that are automatically detected from images. The xMin, xMax, yMin and yMax data properties (See Figure 3) capture the anchor box where a detected object is located in an image. Furthermore, the data property hasConfidence represents a confidence score that is the probability that a defined anchor box contains the detected object.

As the maturity level of the above described risk ontology gradually increases over the course of the project, it will be published on the Github community platform (github.com) to improve the visibility and adoption of the ontology.

4.2. Use of risk database

As described in the previous chapter, the data model defined for describing safety risks is highly connected. In other words, there exists multiple relationships between identified concepts, which sets specific requirements for a selected database technology to store this kind of data. During the recent years, the limitations of traditional databases, in particular the relational model, to cover the requirements of current application domains, has lead the development of new technologies (Angles, 2012). In particular graph databases have increased in popularity. A graph database is a database designed to treat the relationships between data as equally important to the data itself (Kumar, 2019). The main benefits of graph databases include

- Performance - Improved performance by several orders of magnitude compared to traditional database (Dominguez-Sal et al. 2010)
- Flexibility – Can hold data without constricting it to a pre-defined model. The structure of the graph can evolve over time as needs and requirements clarify (Vicknair et al. 2010)

In BIMprove, different safety risk related data is stored using the Apache Fuseki (Yang et al. 2018). Fuseki is a graph database server that enables storing data in an RDF (Resource Description Framework) format and querying it using the SPARQL query language. The data stored in the Fuseki database is structured according to the ontology described in the previous chapter. RDF and SPARQL are powerful, yet complex, ways to store and retrieve data. To flatten the required learning curve, a specifically designed API solution is developed in BIMProve to simplify the storing and acquiring of risk data. A high level architecture of the overall database solution is depicted in Figure 6.

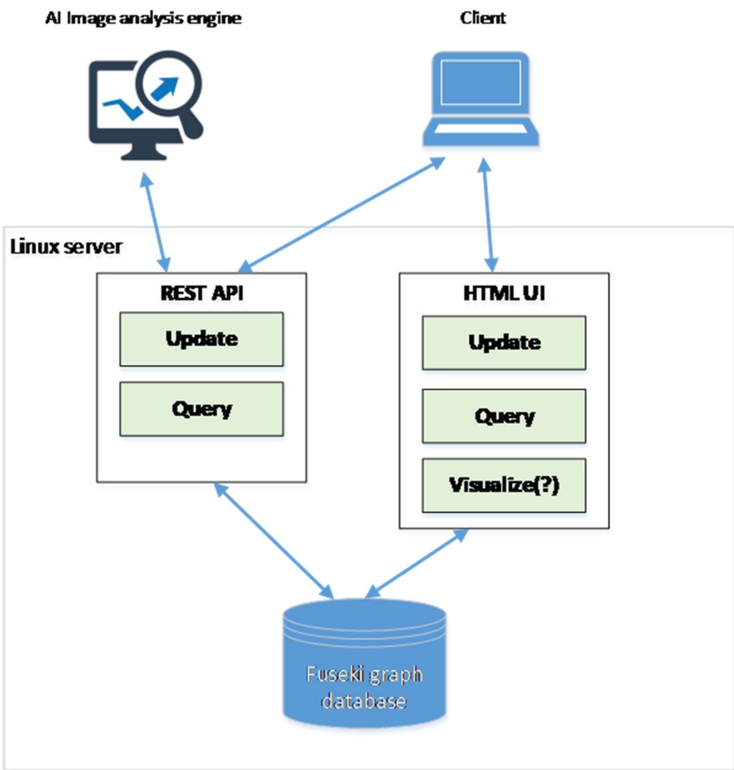

Figure 6. BIMProve database solution for storing and querying risk data

As shown in Figure 6, the simplified API to utilize Fuseki database service contains two access methods. The REST (Representational State Transfer) based API enables other systems and software to programmatically update and query the database. For example, the Automated detection of safety factors and risks module described earlier utilizes this method to access the risk database. The HTML based web user interface enables human users to manage the database contents. It allows, for example, to add new database instances through a simple web page form. Additionally, it enables retrieving data contained by the database either in textual or visual form.

The above mentioned REST API accepts JSON data as input parameters. Figure 7 represents an example JSON structure that defines a risk related object that was identified from an image by the Automated detection of safety factors and risks module. As can be seen, the input parameters follow the properties of the data model described in the previous chapter. The input parameters contain, for example, the ID and URL of the image that was analysed, type of the risk related object and coordinates of the anchor box that specifies the part of the picture the object is located in.

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```json
{
    "imageID":"z9MHIIjZQ0",
    "name":"safetynet",
    "confidence":"0.485",
    "xmax":"925.186",
    "xmin":"481.6767",
    "ymax":"964.23455",
    "ymin":"712.9662",
    "imageURL":"https://bit.ly/3glwtiH",
    "anchorBoxImageURL":"https://bit.ly/3glwtiH"
}
```


Figure 7 Example input data defining a risk related object extracted from an image

An example of the web page UI to access Fuseki database is shown in Figure 8. In this view, results of the image analysis module are represented in a table format. The table lists images and risk related objects identified from the images. The table is sorted based on the image IDs.

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Image database

Image Id	Risk related object	Confidence	xmax	xmin	ymax	ymin	Image URL	Image URL with anchor box
79bdJnMipL	safetynet	0.357	325.767	148.123	431.346	239.687	Image	Image with anchor box
f52-oioNhG	garbage	0.567	986.545	477.566	789.57	567.766	Image	Image with anchor box
K9MHIljZQ0	barrier	0.289	925.186	481.677	964.235	712.966	Image	Image with anchor box
tsoyrxA6S8	barrier	0.234	789.443	345.866	876.312	436.529	Image	Image with anchor box
tsoyrxA6S8	garbage	0.567	234.447	100.566	343.344	97.454	Image	Image with anchor box
z9MHIljZQ0	safetynet	0.485	925.186	481.677	964.235	712.966	Image	Image with anchor box

Figure 8. Screenshot from the Fuseki database web UI

In the following phases of the project, both access methods to the database will be extended and updated to address various requirements of the safety functionalities and worker notifications developed in BIMProve.

5. Worker Notifications

Workers should be notified of dangerous situations at their proximity. In order to preserve the privacy of workers, the notifications will be sent only to the devices that have requested them. The actual process of worker notifications will be presented in the future version of this deliverable.

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