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ASPECTS OF MACHINE LEARNING IN HUMANITARIAN DEMINING PROCESSES

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Abstract: *Machine learning algorithms require high-quality and diverse data to effectively train models. In the context of humanitarian demining, data collection includes gathering information regarding mine locations, types, soil conditions, environmental factors, and any other relevant variables. This data serves as the basis for developing machine learning models. Various machine learning algorithms can be applied in the context of mine detection, and the choice of the appropriate algorithm depends on factors such as the nature of the data, computing resources, and desired performance. Researchers and practitioners can experiment with different algorithms to find the most suitable one for their specific needs. This paper will present a review of some aspects of the application of machine learning elements in the analysis of terrain contaminated with explosives, with an emphasis on processing efficiency and a high degree of reliability of such an approach.*

Key words: *ERW, UXO, machine learning, algorithms, prediction*

1. INTRODUCTION

Humanitarian demining is the process of clearing landmines and other explosive remnants of war (ERW) from areas affected by conflict. It is a dangerous and challenging task, but it is essential to the safety and well-being of civilians. Landmines and ERW are a major threat to civilians in many parts of the world (Mounu Prem at all, 2022). They can cause death, injury, and disability, and they can also prevent people from accessing essential services such as education and healthcare. Humanitarian demining helps to reduce this threat and to make it possible for people to live safely and freely. There are many different organizations involved in humanitarian demining. These organizations include governments, non-governmental

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organizations (NGOs), and private companies. They use a variety of methods to clear landmines and ERW. One of them is manual demining. This is the process of clearing landmines and ERW by hand. It is the most dangerous method, but it is also the most effective. Another approach concern mechanical demining which presents the process of clearing landmines and ERW using machines. It is less dangerous than manual demining, but it is not as effective. Also, canine demining is presents and became innovative approach. Canine demining is the process of using dogs to detect landmines and ERW (P.A. Prada, M.C. Rodríguez, 2015). Landmines continue to kill and injure thousands of people each year, even decades after wars end. The vast majority of victims are civilians, including children. The removal of landmines is a slow and dangerous process, and it is often left to humanitarian organizations.

Humanitarian demining is a complex and challenging task, but it is essential to the safety and well-being of civilians. The organizations involved in humanitarian demining are working to make the world a safer place, one landmine at a time. There is numerous challenge we face in this process. The presence of landmines and ERW is often hidden from view. Landmines and ERW can be difficult to detect and remove. Despite these challenges, humanitarian demining is making progress. The number of landmines and ERW being cleared each year is increasing, and the number of people being killed or injured by landmines and ERW is decreasing (Hagenlocher et all., 2015).

Landmine detection poses numerous challenges due to the nature of these hidden explosive devices and the environments in which they are typically found (The Halo Trust 2011). Landmines come in different types, sizes, and configurations, making their detection more challenging. Some are made of metal, while others are made of plastic or composite materials, which can evade conventional detection techniques. Landmines are typically buried underground, making them difficult to detect visually. They can be concealed under soil, vegetation, or other camouflage materials, further complicating their detection. Many modern landmines are designed with reduced metal content or are completely non-metallic. This makes them difficult to detect using traditional metal detectors, which rely on detecting metal objects. The effectiveness of landmine detection can be affected by various environmental factors, such as soil type, moisture content, temperature, and vegetation density. These factors can influence the signals emitted by detection systems and cause false alarms or missed detections. Detection systems must be able to distinguish between landmines and harmless metallic objects commonly found in the ground, such as rocks or debris. High false alarm rates can lead to reduced efficiency and increased costs. Landmine detection technologies need to be affordable, portable, and suitable for use in various terrains and regions. This can be challenging, especially for developing countries affected by landmines, where resources may be limited. These operations involve inherent risks to the personnel performing the task (Knox, 2017). Ensuring the safety of operators and minimizing the risk of accidental detonation is of utmost importance. Finally, in areas affected by conflicts, landmines are often scattered randomly, making systematic clearance difficult. Inadequate records or maps of mined areas further complicate the clearance process.

Addressing these challenges requires the development of advanced technologies, including ground-penetrating radar, thermal imaging, acoustic sensors, chemical detection, and the use of drones and robotics. It also necessitates collaboration between governments, international organizations, and research institutions to enhance the effectiveness and efficiency of landmine detection methods.

There have been some attempts to develop new technologies to help with landmine clearance, but most of these projects have been unsuccessful. The humanitarian community still relies on outdated technologies, such as metal detectors and bayonets, to find and remove landmines.

There is a need for new and innovative technologies to help eliminate landmines. Multi-faceted demining machines, such as remote-controlled or semi-autonomous robots, could make the demining process safer and more efficient. These robots could eventually perform all of the major stages of landmine clearance, from preparing the ground to removing the mines themselves (Rafique at all, 2019).

In addition to demining machines, other technologies, such as unmanned aerial vehicles (UAVs), Ground penetrating radar (GPR) and advanced image classification and recognition software, can also be used to help find and remove landmines (Lameri at all,2017). These technologies can be used to survey areas for landmines, identify likely mine locations, and even remove mines themselves (Liam at all., 2019). The development and deployment of new technologies to help eliminate landmines is a critical step in the fight against this deadly threat. By investing in these technologies, we can save lives and help communities rebuild after conflict.

Demining robots can be used to detect, remove, and destroy landmines. They are safer than humans and can work in more dangerous areas. Unmanned aerial vehicles are used to survey areas for landmines and to identify likely mine locations. They can also be used to deliver demining robots to remote areas. Advanced image classification and recognition software can be used to identify landmines in images and videos. This can be used to prioritize areas for clearance and to avoid unnecessary excavation. These are just a few examples of how new technologies can be used to eliminate landmines. As these technologies continue to develop, they will play an increasingly important role in the fight against this deadly threat.

2. MACHINE LEARNING CONCEPT

One of the major challenges in demining operations is the allocation of limited resources. The size of the area to be cleared is often much larger than the resources available. Additionally, the location of contaminated areas is often unknown, making it difficult to plan the deployment of resources effectively (Goodfellow at all, 2015). Currently, the allocation of demining resources mainly depends on non-technical surveys, demining dogs, and local knowledge. Non-technical surveys involve collecting information about the area to be cleared, such as its history of conflict and the type of terrain. One of powerful tool for solving these challenges is machine learning.

Machine learning is a subset of artificial intelligence (AI) that focuses on the development of algorithms and models that enable computers to learn from data and make predictions or decisions without being explicitly programmed. It involves teaching machines to improve their performance on a task as they are exposed to more data. Machine learning is a powerful tool with applications across various industries, including healthcare, finance, transportation, and more. Its continuous development and integration with other technologies like big data and cloud computing open up new possibilities for innovation and problem-solving. However, it's important to approach machine learning projects with a clear understanding of the domain, data, and potential challenges to achieve successful outcomes.

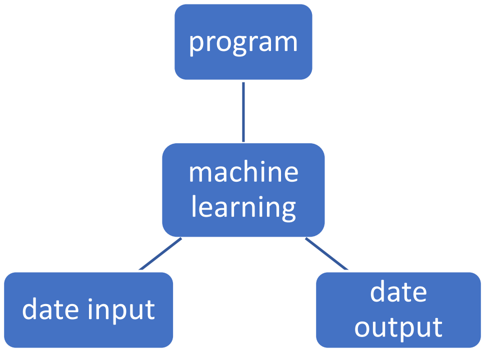

Figure 1. Concept of machine learning
Source: Authors

Machine learning algorithms use historical data as input to predict new output values. There are three main types of machines learning supervised learning, unsupervised learning and reinforcement learning. Supervised learning is a type of machine learning requires labeled data, which means that the output values are known. The algorithm learns to map the input data to the output values (Goodfellow at all, 2015). Unsupervised learning is type of machine learning does not require labeled data. The algorithm learns to identify patterns in the data without knowing the output values. Reinforcement learning presents type of machine learning that allows software applications to learn by trial and error. The algorithm is given a reward for taking actions that lead to desired outcomes and a penalty for taking actions that lead to undesired outcomes. Machine learning is a rapidly growing field with many potentials in humanitarian demining (Bajic & Potocnik, 2023). As the technology continues to develop, it is likely to have a major impact on our lives. Classical machine learning algorithms are often categorized by how they learn to become more accurate in their predictions.

3. RESULTS AND DISCUSSION

In first step, we try to create a date base of 3d models of mine used in this region in the past and now. In practice there are two main types of 3D scanners: contact scanners and non-contact scanners. Contact scanners use a physical probe to scan the surface of the object, while non-contact scanners use lasers or other sensors to scan the object without touching it. IN our case we used *Range vison smart 3D scanner*. For UXO in this case PM1 mine, a non-contact scanner is typically used, as it is less likely to damage the UXO model. The scanner should be positioned so that it can capture all of the details of the UXO model. This may require moving the scanner around the UXO model or rotating the UXO model. For best results, the scanner should be positioned perpendicular to the surface of the UXO model. The number of points that are scanned will depend on the desired accuracy of the 3D model. For most applications, a few thousand points per square inch will be sufficient. However, for applications that require high accuracy, such as designing mine, a higher number of points may be needed.

There are a number of software programs that can be used to process 3D scan data. The specific software that we can use will depend on the type of 3D scanner that we have and the desired output of the processing. The 3D model should be inspected to ensure that it is accurate and complete. This can be done by comparing the 3D model to the actual type of mines. The mine should be clean and free of dirt and debris to ensure that the 3D scanner can capture accurate data. The scanner should be properly calibrated to ensure that the scan data is accurate. The scan data should be processed carefully to ensure that the 3D model is accurate and complete.

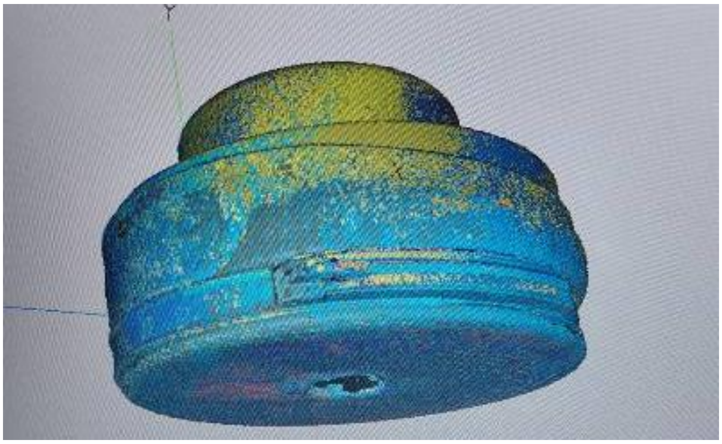

Figure 2. 3D model of PM 2 mine projection 2
Source: Authors

There are many different 3D modeling software programs available, each with its own strengths and weaknesses. Some popular options include Blender, Autodesk Maya, and SolidWorks, Scan center NG 2021. In our case we have used the last one.

After created the 3D models, we exported them into a format that can be imported into a database. Some common formats for 3D models include STL, OBJ, and FBX. We decided for, *.STL format. In next step 3D models in this format have been imported into a database, created by database management system (DBMS) MySQL. All models have been imported by DBMS's import tool.

After that, some of the standard set of algorithms for comparation between models and pictures could be applied. We can use a convolutional neural networks (CNNs) CNNs are a type of machine learning algorithm that are well-suited for image processing tasks. They can be used to extract features from images, such as edges, textures, and shapes. These features can then be used to compare the 3D model and the pictures.

In the case that UXO needs to be analyses through underlying structure of date, we can use autoencoders. This is a type of machine learning algorithm can be used to create a compressed representation of the 3D model and the pictures. This compressed representation can then be used to compare the two. Also, we are available to use generative adversarial networks (GANs) GANs are a type of machine learning algorithm that can be used to generate realistic images. They can be used to generate images of the 3D model and the pictures. These images can then be compared to each other to determine the similarities and differences between the two.

Figure 3. UXO, detected by UAV and H20T DJI camera
Source: Authors

The best method will depend on the specific application that we are using the comparison for. For example, if you are simply trying to see if the 3D model matches the pictures, then CNNs may be sufficient. However, if we need to quantify the differences between the 3D model and the pictures, then we may need to use a more sophisticated method, such as autoencoders or GANs.

4. CONCLUSION

Currently, the allocation of demining resources mainly depends on non-technical surveys, demining dogs, and local knowledge. Non-technical surveys involve collecting information about the area to be cleared, such as its history of conflict and the type of terrain. Demining dogs are trained to detect landmines by their scent. Local knowledge can be used to identify areas that are likely to be contaminated. However, these methods are not always reliable. Non-technical surveys can be time-consuming and inaccurate, and demining dogs can be fooled by other objects that smell like landmines. Local knowledge can be outdated or inaccurate.

As a result, there is a need for more reliable methods for allocating demining resources. One promising approach is to use machine learning. Machine learning algorithms can be trained to identify contaminated areas based on historical data and other factors. This can help to improve the accuracy of the allocation of resources and make demining operations more efficient.

Machine learning can be used to identify patterns in historical data on landmine clearance. This data can be used to train machine learning algorithms to predict the likelihood of an area being contaminated. Also, machine learning can be used to analyze images and videos of an area to identify potential landmines. This can be done by identifying objects that are consistent with the appearance of landmines. Machine learning can be used to develop models of the behavior of landmines. This information can be used to predict where landmines are likely to be located. By using machine learning, it is possible to improve the accuracy of the allocation of demining resources and make demining operations more efficient. This can help to save lives and protect communities from the threat of landmines.

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