A location-based model using GIS with machine learning, and a human-based approach for demining a post-war region

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ABSTRACT

Locating and removing landmines and other ERW (Explosive Remnants of War) is dangerous, hazardous, and time-con-suming. It requires implementing multilevel on-site surveys: general non-technical surveys to mark the areas affected and technical surveys to determine the perimeter of related mine-fields. This paper introduces a landmine location-based pre-diction model, combining military experience with machine- learning techniques and spatiotemporal data, by introducing a new approach for area selection and adding military-based features for context modelling and model training. Besides predicting landmine's location areas, this model classifies the affected regions by priority and difficulty of clearance, in such a way as to minimise the long time needed by surveys and reduce the danger related to that task, thus providing the clearance organisations with a good resource allocation for their operations. We applied several machine learning tech-niques that combine Support Vector Machine (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGBOOST), tak-ing into consideration the imbalanced data problem and tweaking for the best performance and accuracy. The experi-mental results show that the model has the potential to provide reliable predictions and valuable services for demin-ing operations on the field.

KEYWORDS

Location-based model; machine-learning; demining

1. Introduction

Landmines are explosive devices that are designed to be placed on or in the ground to disable or kill enemy forces or civilians. They are often used in war or conflict situations, and they can remain active and dangerous long after the conflict has ended, posing a significant threat to civilians, and hindering the recovery and development of affected areas. In total, there have been 2374 reported casualties of mines or other explosive remnants of war in Lebanon, of which 631 people were killed (from 1971 until the beginning of

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2023). Humanitarian demining is the process of removing landmines and other explosive remnants of war from areas affected by a conflict. The goal of humanitarian demining is to reduce the risk of injury or death to civilians, facilitate the return of refugees and displaced persons, and support long-term development efforts in affected areas. It involves several steps, including surveying and mapping affected areas to identify the locations of landmines, clearing and removing the mines using specialised equipment and trained personnel, and destroying the mines in a safe and controlled manner. The work of humanitarian demining is often done by specialised organisations, such as the United Nations Mine Action Service (UNMAS), Non-Governmental Organizations (NGOs), and national demining programmes. These organisations use a variety of methods and tools to identify and remove landmines, including mine-sniffing dogs, metal detectors, and manual probing (Geneva International Centre for Humanitarian Demining GICHD 2010a, 2010b).

Humanitarian demining is a challenging and dangerous task, as landmines are often difficult to detect and may be hidden in densely populated areas or in locations that are difficult to access. However, the work of demining is critical to reducing the harm caused by landmines and supporting long-term development and recovery efforts in affected areas. Lebanon faces a dual mines threat: one along its southern border and another one within the country itself, both of which were laid by different parties during a civil war. The whole issue is the responsibility of the LMAC (Lebanon Mine Action Center), the Lebanese national authority responsible for humanitarian demining.

The cost of humanitarian demining can vary depending on factors such as the size of the area to be cleared, the type and density of contamination, and the availability of resources. Humanitarian demining faces several challenges, including:

- **Safety**: Humanitarian demining is a life-threatening activity that puts people's lives at risk. Safety measures must be taken, for instance, the use of protective equipment.
- **Detection**: Landmines and other explosive remnants of war can be difficult to detect, especially if they are buried underground or hidden in vegetation. Detection technologies such as metal detectors, ground-penetrating radar, and sniffer dogs are used to locate landmines.
- **Clearance**: Once landmines are detected, they must be safely removed or destroyed. Clearance methods include manual clearance, mechanical clearance, and mine detection dog clearance.
- **Resources**: Humanitarian demining requires significant resources, including funding, equipment, and trained personnel. Careful study of the contaminated area must be undertaken to ensure good distribution of resources.

Mining and demining are military tasks, and the most relevant feature that defines a military task is its spatiotemporal context, i.e. its precise area of application in a well-defined time constraint. Landmine prediction is a location-based task aiming to deliver demining operations to the exact location of mined areas, and to treat them at a convenient time. Besides that, military expertise plays a role in the context modelling of spatial data to classify the predicted mined areas by priority of clearance, and difficulty of clearance, with the same objective to assist the clearance operations in achieving their tasks efficiently.

The research presented in this paper introduces a predictive model for the location of landmines. It is based on an application and comparison study of machine learning techniques applied to historical data coupled with spatial data. The model is designed to predict the areas where landmines are likely to be found and classify these areas by priority and difficulty of clearance. This information is useful for organisations that clear landmines in situ as it allows them to allocate resources more efficiently and safely. The rest of the paper is organised as follows. Section 2 briefly discusses the related work. Section 3 presents the baselines that motivate the choice of the comparative algorithms and introduces our methodological approach, and Section 4 the implementation principles. Finally, Section 5 presents and discusses the results, and Section 6 concludes the paper and outlines a few directions for further work.

2. Related work

Nowadays many organisations combine Geographical Information Systems (GIS) and Machine Learning (ML) to derive valuable insights and predictions from spatial data (Baur et al. 2021; Krtalic and Bajic 2019; Milton and Roumpani 2019). When GIS and ML are used together, the analysis and interpretation of large, unstructured, and complex spatial datasets are facilitated. By using ML algorithms, GIS can identify patterns and relationships in the data that might be missed by common GIS analysis techniques. For example, ML can be used to classify land use types from satellite imagery, predict urban growth patterns, and identify areas at risk of mines, flooding, or other natural disasters (Digra, Dhir, and Sharma 2022; Mosavi, Ozturk, and Wing Chau 2018). A wide range of advanced data analytics has been applied to geographical and semantic properties to deliver location-based services such as store recommendations (Shahriari-Mehr et al. 2021), contact tracing (Gupta et al. 2021), archaeological prospection (Verschoof-van der Vaart et al. 2020), and building attractions (Elariane 2022). However, to the best of our knowledge, context-based demining operations haven't yet been considered.

Many studies combine GIS and ML to predict rare event occurrences, such as mined areas (Rafique et al. 2019) with relatively good figures (i.e. accuracy 89%), earthquake vulnerability assessment (Shafapourtehrany et al. 2022) (i.e. accuracy 96.2%), and wildfire (Gohlamnia et al. 2020) (i.e. accuracy 88%). GIS analytic techniques are used to extract independent features from historical and topographic data, such as 3D data (e.g. elevation and hill slope), distances to different features (e.g. borders, roads, forests, rivers), population density, and vegetation classes identified by remote sensing NDVI images. However, according to military experts, the training samples are of relatively low prevision when dealing with mines (e.g. 4500 m (Sun Yoo et al. 2020)), as many minefields have an area of less than 1000 m2. Other studies focus on the usage of drones fitted with magnetometers and ground penetrating radars to detect the locations of landmines (Barnawi et al. 2022; Colorado et al. 2017; Garcia-Fernandez et al. 2019; Jangra and Dalal 2020), but still, these approaches are limited by sensor capacities and the one of integrating soil properties. However, as the usage of drones is fast growing, they will be considered complementary to our study after predicting the main mined areas first using historical data and ML, and after identifying the potential location of each mine.

A study reviews landmine detection approaches and especially how deep learning can be integrated to enhance their accuracy (Hamad, Kolo, and Balzter 2018), this paper incorporates GIS with machine learning to give better results and understanding of the correct usage of demining tools and methods. Another study presents in a different way the assessment of demining operations' impact, as it emphasises the bad effect of heavy demining machinery on the soil and the remarkable change in the land cover due to their usage as identified by a combination of GIS and remote sensing techniques (Malik, Singh, and Harode 2017). In fact, as mining and demining are military-based operations, most if not all these studies do not consider military expert knowledge, this has been a major drawback.

Therefore, our study considers smaller regions to generate a relatively acceptable accuracy (i.e. the number of samples' number should increase with the size of the entire area of interest and decrease conversely). Moreover, military features and expertise are used as baselines when selecting the areas to mine, as they ensure the selection of an appropriate region where mines are supposed to be encountered and the identification of relevant areas to study. The performance of recent and extended machine learning algorithms is experimented with to deliver the most appropriate accuracy to the whole modelling and processing approach, and relevant support for location-based demining operations.

3. Methodological background

3.1. Machine learning comparison principles

ML algorithms are commonly applied to predictive processes involving several data dimensions as in our case. Our approach specifically retains a combination of approaches that together are relatively efficient in terms of usage, high accuracy, robustness to noise and outliers, built-in feature selection, non-linearity handling, scalability, and execution time, that is, SVM (Support Vector Machine), RF (Random Forest), and XGBoost. SVM and RF were used to properly classify similar problems (Gohlamnia et al. 2020; Shafapourtehrany et al. 2022), while XGBoost is a promising algorithm in classification for different problems, well known for the speed of execution and good accuracy (Malik, Singh, and Harode 2017).

SVM is a powerful ML algorithm used for classification, regression, and outlier detection. It is a supervised learning method that constructs a hyperplane in high-dimensional space to separate the classes. The hyperplane is chosen in such a way that it maximises the margin, which is the distance between the hyperplane and the closest points of each class (Awad and Khanna 2015). SVM is one of the most accessible algorithms and has been used in a previous comparable study (Biau and Scornet 2015). Random Forest (RF) and XGBoost are both powerful ML classifiers used for solving complex classification problems. Both classifiers belong to the family of set methods, which means they combine the results of multiple models to make predictions (Zhang, Jia, and Shang 2022).

Random Forest is a type of decision tree algorithm that constructs multiple decision trees at training time and aggregates their predictions to generate the final output. Random Forests are effective in handling noisy data and reducing overfitting, and they can handle large and high-dimensional datasets. Random Forests also provide feature importance metrics to identify which features are most important in making predictions.

XGBoost, or Extreme Gradient Boosting, is an advanced implementation of a gradient-boosting algorithm that creates multiple decision trees sequentially. XGBoost is designed to improve the performance of traditional gradient boosting algorithms by optimising the computation time and memory usage. XGBoost uses regularisation techniques to reduce overfitting and provides feature importance metrics (Fryer, Strumke, and Nguyen 2021).

Our approach uses and compares the ML techniques explained above (SVM, RF, and XGBoost) due to their popularity in such rare events prediction especially life-threatening ones such as mines, their accuracy, and their speed of execution especially for XGBoost. The metrics watched for are accuracy, precision, recall, area under curve, and confusion matrix.

- Accuracy is defined as the ratio between the well-classified samples (true positives and true negatives) and the total number of samples.

- Precision is defined as the ratio between all the instances that were correctly classified in the positive class against the total number of actual instances classified in the positive class.
- Recall is defined as the ratio between all the instances that were correctly classified in the positive class against the total number of actual members of the positive class.
- Area under the curve is a plot of the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings.
- Confusion matrix is a table that is often used to describe the performance of a classification model on a set of data for which the true values are known. It gives the True Positive observations (TP, correctly predicted as positive), True Negatives (TN, correctly predicted as negative), False Positive and False Negative (FP and FN, wrongly predicted as positive and negative respectively).

These algorithms are certainly tweaked for best parameters using the Scikit-learn library (GridSearch CV), where for each algorithm a set of parameters is tested and those giving the best results are chosen.

The rare event type of mining (i.e. imbalanced data: where the number of negative classes (value 0) is much greater than the number of positive classes (value 1)) is taken into consideration by first applying the military features (visibility and distance to confrontation lines) to correctly select the study area. Therefore, appropriate techniques (such as SMOTE() and BalancedRandomForest) are applied to deliver reliable results.

To predict the results on unseen data, cross-validation (precisely Stratified Cross Validation) is applied, where the original dataset is split into n datasets, and each time trained on *n*-1 datasets and tested on the remaining dataset considered as the unseen dataset.

The algorithm giving the best results in mined area prediction is then applied to class the predicted mined areas over their difficulty and priority of clearance, respectively. Priority of clearance defines the importance to start demining of a certain minefield in relevance to its socioeconomic impact, whereas the difficulty of clearance represents how difficult will be to access and clear that minefield. Before that, the thresholds separating the difficulty and priority classes are well defined. For the priority, they are defined relative to their distances from land-use categories, infrastructure, and population (roads, urban areas, forests, agricultural areas, deserted areas, and population density), in such a way that the ones giving the most socioeconomic impact get the first priority of clearance. For the difficulty of clearance, they are defined as a function of the soil vegetation type (high or low vegetation), the slope, and the elevation of the terrain; the ones with high vegetation and higher slopes and high elevation will be the most difficult to clear. The predicted areas are prioritised into three classes (i.e. first, second, and third) and classed into three classes for the demining difficulty (i.e. hard, moderate, and easy). These two classes (priority and difficulty of clearance) are introduced by the military expertise as they are heavily used before conducting demining operations, to conduct these operations in a socioeconomic manner with favourable allocation of resources.

On the other hand, landmines are planted by military-qualified personnel, who have to well study the area of operations, define its features, and precise the source of threat that may be caused by enemy infiltration or penetration, and block the vulnerable areas by mines. This is basically done by defining the area of conflict and its boundaries called confrontation lines (usually within a distance of 1000 m from these lines), the observation posts along those lines, and then performing visibility analysis from the observation posts to reveal the parts visible and invisible from these posts. The latter is more susceptible to being mined as they are hidden from observation. Besides that, mines are too dangerous and heavily pollute the land, so they must be laid carefully where they are just needed. So, military-qualified personnel are needed to assist in the prediction and clearance of mined areas.

Those military features are identified by going back to historical data regarding the conflict posts occupied by different parties and giving the exact location of confrontation lines between those posts. The objective is to extract the features with the 3D data available in the study area to compute the visibility from posts and distance to confrontation lines. Our approach has the peculiarity of integrating additional important properties not considered in previous work (e.g. Rafique et al. (2019)) such as confrontation line, visibility, priority, and difficulty. As the number of training samples plays a major role in ML algorithm accuracy, the number of samples used in our study has largely increased.

3.2. Methodological principles

The aim of our study is to predict mined areas in a post-war region as a first step and to classify those predicted areas into difficulty and priority of clearance in the second step. To achieve this goal, our approach combines military expertise, ML, and GIS, and is algorithmically formulated as follows:

3.2.1. Data preparation

- Carefully define the study area close to the confrontation lines, and the observation posts along those lines.
- Divide the area into small samples (10×10 m boxes).
- Gather the GIS infrastructure, 3D, and population data, and use GIS techniques to extract the spatial features within the study area: Distance to confrontation lines, Visibility, Slope, Elevation, Distance to urban areas,

Distance to agricultural areas, to deserted areas, Distance to forests, Distance to roads, and Population density.
- Add the features regarding the priority and difficulty classes.
- Export the data to CSV format readable in ML.

3.2.2. Data processing

- Hyper-tune the parameters for the three ML algorithms and choose the best parameter sets.
- Apply the algorithms and choose the one giving the best results in mined area prediction.
- Apply the same algorithm again on the areas predicted as mined to classify them into priority and difficulty of clearance.

3.2.3. Results interpretation

- Export the resulting datasets to a location-based, readable GIS format.
- Interpret and analyse the results.
- Deliver the data to demining organisations to start the clearance process.

As shown in Figure 1, the first principle applied is to select the study area by military standards and divide it into small samples thus increasing the number of elementary areas but maximising the appropriateness of the evaluation process. The second one is the military expertise whose principle is to add visibility from observation posts and confrontation line constraints to existing mined areas and common geographic features. These include distances from different land aspects (forests, urban, transportation, …), and population characteristics, assign priorities and difficulty of clearance, and export the resulting vector to CSV file used as input to machine learning algorithms. The third principle is to apply the classifiers SVM, RF, and XGBoost to predict the suspected areas for mining and then to classify those areas by priority of clearance and difficulty of clearance.

4. Implementation

4.1. Data preparation

The first step of the implementation is to gather data from different sources related to all the features needed in the study. Common features and military-specific features are identified using military expertise to properly select the area of interest or study area, in a way that is close to the confrontation lines to give sense according to military standards (i.e. areas chosen to be mined). This specific approach to area selection is applied by military-qualified officers on the tactical level, working within the conflict area to reveal its military geographic aspects and then select the appropriate locations suitable for mining. The

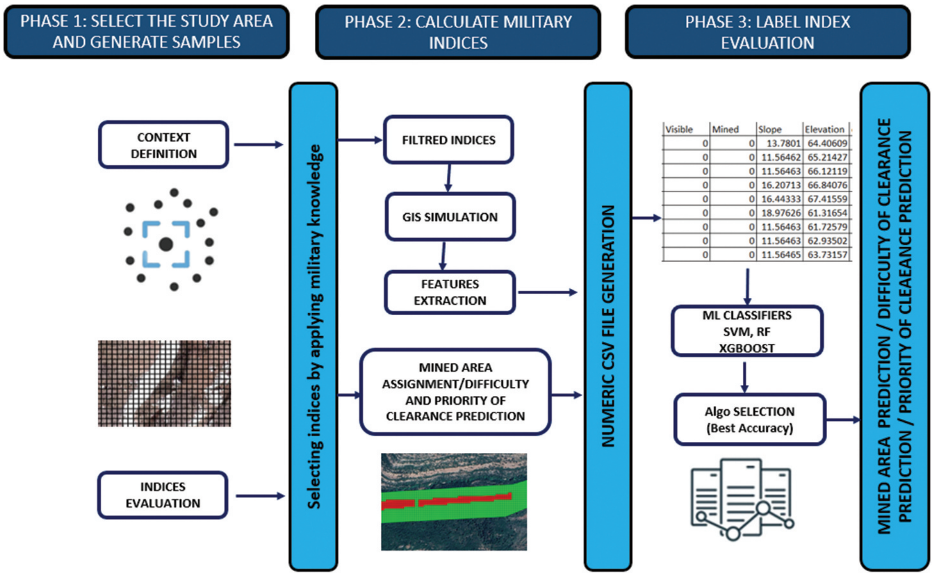


Figure 1. Modeling principles and workflow.

selected area is then structured into small samples of 10 × 10 m as a key feature to obtain better accuracy in machine learning algorithms. This is done by generating a grid of 10 × 10 to fill the selected area. To class these samples as mined or not mined, we assigned a value of 1 to the polygon covering a mined area, and a null value where no mines are present. The data is divided into two parts: the sample layer (10 × 10) to be filled by features and then transformed as input to ML algorithms, and the layers to be used as input for the features (from where the values are obtained). The underlying layers are first transformed into elementary units of 10 × 10-pixel size, and then into proximity layers where each pixel is assigned the distance to the proximity feature. Corresponding values are then allocated to the sample study area layer.

Military experts define the priority of clearance according to distances from mined areas to different features (e.g. urban areas, cultivated areas, deserted or unpopulated areas), population density in proximity, and other features. For instance, the closer the mined zone is to urban areas, the higher priority it is given; a cultivated area is given a higher priority than a deserted area, and then the higher the population affected by the mined area, the higher its priority of clearance is given. Accordingly, mined areas are classified by priority of clearance depending on their socioeconomic impact. Elevation data and slope are then used by military experts to classify the mined areas by difficulty of clearance.

For instance, distance thresholds are between 500 and 2500 metres, population thresholds are between 200 and 800 persons per square km, and priority values are given within these intervals (e.g. priority value 3 for distance ≤500 m, 2

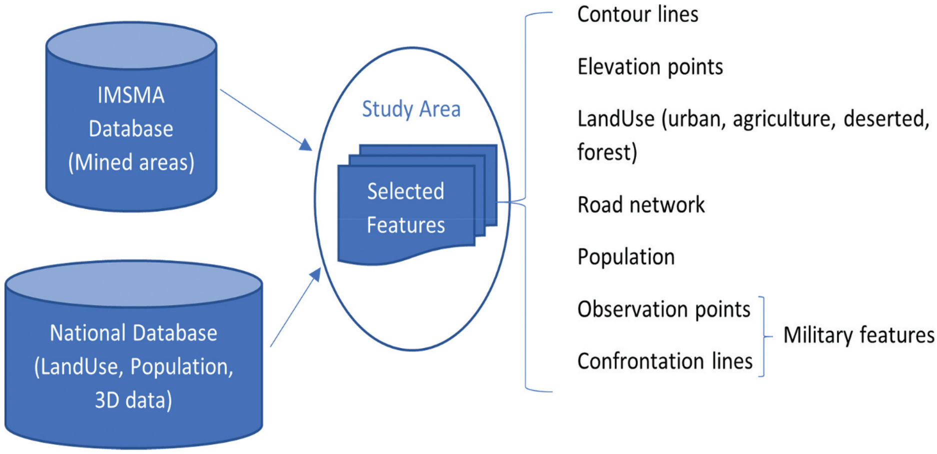


Figure 2. Data integration principles.

between 500 m and 2500 m, 1 for distance ≥2500 m). Similar steps are applied for the remaining features (i.e. elevation, slope), and priority values are given similarly. Finally, priorities are aggregated and classified into three classes (IsMinded, Priority of clearance, difficulty of clearance) using ten independent features (IsVisible, Distance to confrontation line, Slope, Elevation, Distance to Forests, Distance to Urban Zones, Distance to Deserted Areas, Distance to Agricultural Areas, Distance to Roads, and Population Density) and using around 630,000 samples or polygons of 10 m side covering the study area. The data preparation outputs are transformed into an adequate format and passed to the ML algorithms mentioned above (SVM, RF, and XGBoost), tweaked for best parameters, and classified as mined or not mined, while these algorithms are finally evaluated in terms of accuracy to class mined areas by priority and difficulty of clearance.

As shown in Figure 2, the data gathering is accomplished from local databases: LMAC for mined areas and the national database for other features, including contour lines and elevation points, road network, population, land cover and land use, confrontation lines, and observation points.

The minefield data is in shapefile format and accessible from the Information Management System for Mine Action (IMSMA) in the LMAC, and the remaining data is stored in a PostGIS database in vector data format and accessible from within the army network. The study area is chosen in a way to cover the entire country, so it consists of four areas: one along the southern border where the Israeli army planted mines, and three other areas within the country where different militias were acting. Those areas cover a distance up to 1 km from the different confrontation lines and are processed as a grid of polygons of 10 metres sides (around 630,000 samples, i.e. rows in the attribute table), and then a buffer zone of 10 km is added to select certain features. Figure 3 shows the study area which consists of four parts covering the country from South to North. Figure 4 shows the 10×10 samples or the grid of 10 metres and the

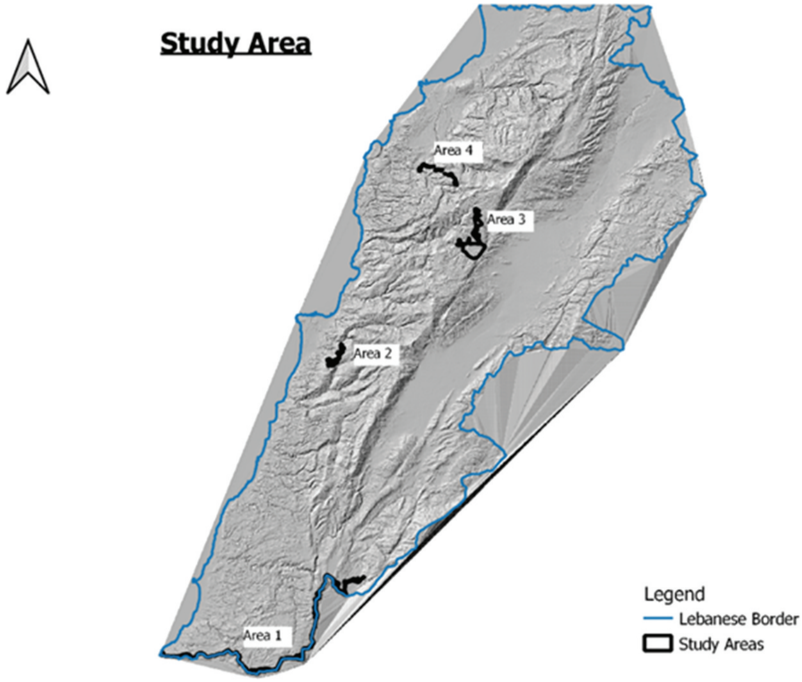
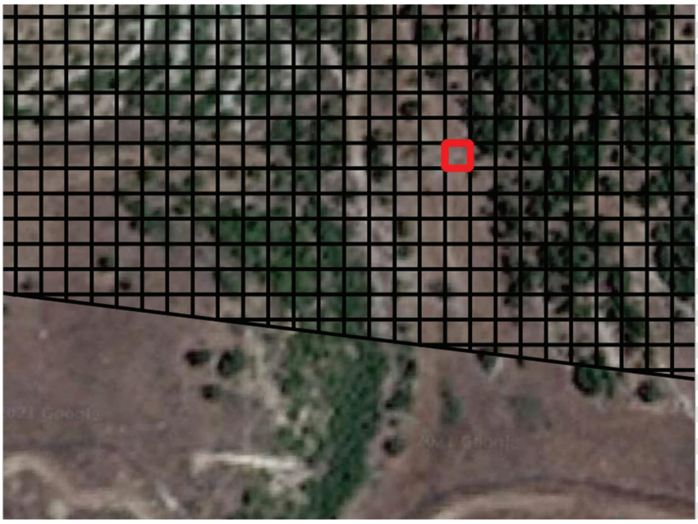


Figure 3. Study area.

features assigned to each grid. Figure 5 gives an example of confrontation lines and observation points, and Figure 6 shows the visible areas from an observation post, which have a trivial role in area selection by converging to the areas with high priority of mining as are not visible from observation posts. The map outputs (i.e. Figures 3-6) are generated by the open-source GIS software for map production and analysis, Quantum GIS (QGIS).

Each of the vector features corresponding to the input data is transformed into an elementary unit whose value is extracted and added to the vector containing the samples. The Digital Elevation Model (DEM) derived from contour lines and elevation points is used to perform visibility analysis from the observation posts (i. e. to determine the areas visible and not visible), and also to create the slope layer. The features added to the sample vector are categorised as distances from each polygon grid (10×10) to relevant features (i.e. distance to urban zones, forests, deserted areas, agricultural areas, confrontation lines, and roads), population density in the area up to 10 km from the study area, 3D derived data (i.e. visibility from observation posts, slope, and elevation). Two additional features are added as a function of the preceding variables, that is, priority of clearance and difficulty of clearance, to train the predictive model. Table 1 illustrates the data sample values, where Fid represents the unique cell ID.

After preparing the data, the obtained ratio of positive samples (i.e. mined, having a value of 1) to negative samples (i.e. not mined, having a value of 0), is 1/3.



fid	32183556
isMined	0
Slopemax	36.61762619018
Elevationmean	681.4425659179
dist_to_urbanmax	1530
dist_to_agrimax	466.6904602050
dist_to_desertmax	2588.358642578
dist_to_forestmax	0
density_per_sqkmmax	148
difficult_slope	4
difficult_elev	2
priority_DstForest	3
priority_DstUrban	2
priority_DstAgri	3
priority_DstRoad	3
priority_DstDesert	3
priority_Dsity	1
difficulty	6
difficulty_classes	3
priority	15
priority_classes	1
isVisible	0
priorities	0
difficulties	2
voisinage_max	0
dist_to_vpmean	615.7649568910
earlyfindings	0
dist_to_confrontation...	216.8155822753
dist_to_roadsmean	211.5910002136
SlopeAstermean	7.292477783440
isForestmean	1
difficulties2	2

Figure 4. Study area samples (grid 10x10).

4.2. Parameters settings and tuning

The process of combining the parameters of an ML algorithm is an important aspect of model selection and configuration. It involves finding the best combination of data preparation schemes, learning algorithms, and model hyperparameters for a given predictive modelling task, so controlled experiments must be performed to discover what works best for a given dataset. This was introduced by the envelope of military expertise, so data preparation, learning algorithm, and algorithm hyperparameters are combined for a global optimisation task. After preparing the data and filling in all the required features, as well as the priority and difficulty classes, ML is used to build an appropriate model and teach it to predict the correct classes.

The three classifiers chosen in Section 3 due to their wide usage and speed of execution are tested to choose the best one fitting our data: SVM, RF, and XGboost. As the nature of data in real situations is slightly imbalanced, BalancedRandomForest (which is an implementation of the Random Forest algorithm that is designed to address the issue of class imbalance in the training data), the variable scale_pos_weight (a parameter in XGBoost that controls the balance of positive and negative weights, useful for imbalanced classes), and SMOTE (used in SVM to increase the number of cases in a balanced way) are used to tackle the imbalanced data problem. All of these three classifiers are tuned for best parameters using GridSearchCV (which is a process that searches exhaustively through a manually specified subset of the hyperparameter space of the targeted algorithm), and the following values as best hyperparameters were found:

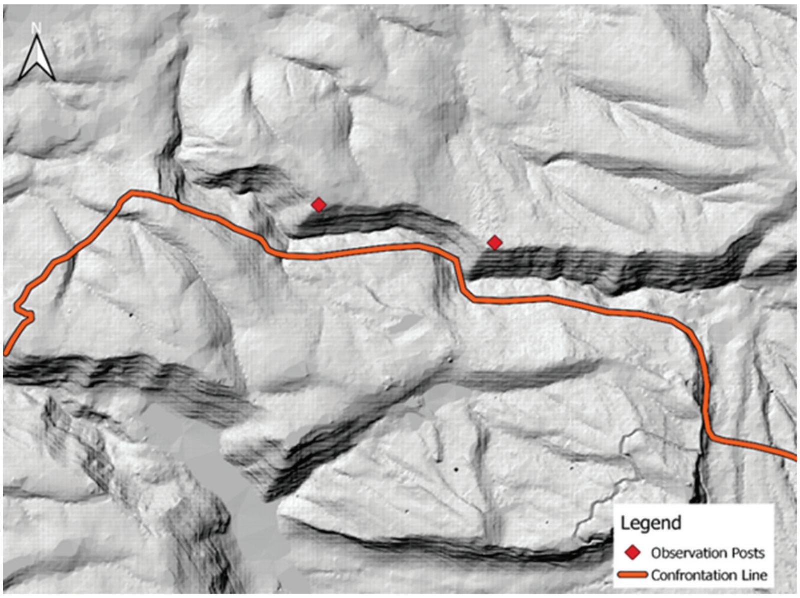


Figure 5. Confrontation lines and observation posts.

- SVM: kernel=rbf, C = 10, and gamma = 0.01
  - rbf is a nonlinear kernel and measures the similarity between two data points as a function of the Euclidean distance between them.
  - C parameter adds a penalty for each misclassified data point.
  - Gamma parameter controls the distance of influence of a single training point.
- RF: n_estimators = 1000, max_depth = 45, max_features = 0.9, random_state = 10.
  - n_estimators is the number of trees in the forest.
  - max_depth is the maximum depth of the tree.
  - max_features is the number of features to consider when looking for the best split
  - random_state controls both the randomness of the bootstrapping of the samples used when building trees.
- XGboost: colsample_bytree = 0.9, gamma = 3.10508, max_depth = 25, min_child_weight = 4, reg_alpha = 37, reg_lambda = 1.80918, n_estimators = 1000, scale_pos_weight = 2.
  - colsample_bytree controls the number of features (variables) supplied to a tree.
  - gamma controls regularisation (or prevents overfitting).
  - max_depth controls the depth of the tree.
  - min_child_weight controls when the tree splitting stops.

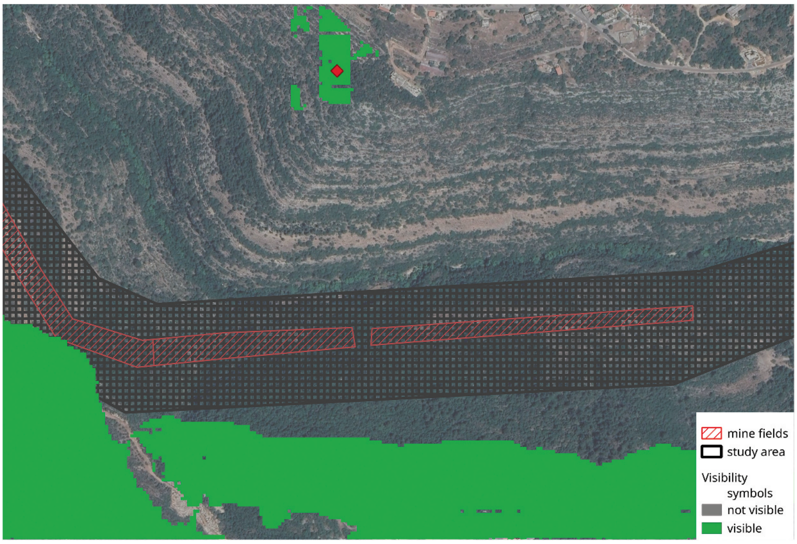


Figure 6. Visibility from an observation post.

- reg_alpha controls L1 regularisation term on weights.
- reg_lambda controls L2 regularisation term on weights.
- n_estimators is the number of gradient-boosted trees.
- scale_pos_weight controls the balance of positive and negative weights.

The parameters mentioned above are selected for each specified algorithm as they have a great influence on its accuracy (e.g. max_depth or the path between the root node and the leaf node, the number of trees in the forest, the max_features or the number of features to take into account to make the best split), and ranges are passed to the GridSearchCV to choose the best combination for each one.

After the prediction of mined areas, the resulting zones identified as mined are selected and extracted from the whole dataset, and reclassified according to priority of clearance, and difficulty of clearance. Accordingly, the data is ready for delivery to demining organisations to start the clearance process, in a safe and socio-economic way.

5. Experimental results

In machine learning, to interpret the results of a classification algorithm, the Shapley value (Shahriari-Mehr et al. 2021), a concept from cooperative game theory, is often applied. The Shapley value allocates the contribution of each player in a cooperative game, considering all possible combinations of players. The idea behind Shapley values is to assign a value to each feature that represents the average marginal contribution of that feature across all possible

Table 1. Data sample structure.

fid	Visible	Mined	Slope	Elevation	dist to urban	dist to agriculture	dist to desert	dist to forest	dist to roads	dist to confrontation	population density	difficulty classes	priority classes
12815	0	0	13.7801	64.40609	2745.778564	3599.125	60	0	20.61552811	90	148	1	2
12816	0	0	11.56462	65.21427	2745.778564	3599.125	60	0	25	78	148	1	2
12817	0	0	11.56463	66.12119	2745.778564	3641.387207	67.08203888	0	29.15475845	72	148	1	2
12818	0	0	16.20713	66.84076	2770.73999	3641.387207	67.08203888	0	26.92582321	63	148	1	2
12819	0	0	16.44333	67.41559	2770.73999	3641.387207	67.08203888	0	26.92582321	51	148	1	2
26121	0	0	18.97626	61.31654	2696.164063	3579.944336	67.08203888	0	15.81138802	129	148	1	2
26122	0	0	11.56463	61.72579	2720.918945	3579.944336	67.08203888	0	20	123	148	1	2
26123	0	0	11.56463	62.93502	2720.918945	3579.944336	67.08203888	0	22.36067963	111	148	1	2
26124	0	0	11.56465	63.73157	2720.918945	3599.125	90	0	26.92582321	102	148	1	2

feature combinations. By doing so, we can understand how each feature contributes to the prediction and gain insights into the model's behaviour and feature importance. The Shapley value can be computed using various methods, such as the Shapley sampling values, Kernel SHAP, or Tree SHAP, depending on the nature of the model and the specific problem at hand. By using Shapley values, we can perform feature importance analysis, explain model predictions, and gain insights into which features have the most impact on the model's output. This information can be useful for model debugging, feature selection, or understanding the underlying relationships in the data.

Figure 7 shows the contribution of our model features in the prediction results in descending order for the RF classifier. As you can see, the Distance to Forests and the Elevation gave the highest contribution, and the Visibility the lowest which is logically mathematically speaking, because Visibility is a binary value (visible 1 or invisible 0), while the other features have real values (distances), but in terms of military importance, the visibility is the most important as previously discussed:

All experiments have been conducted on top of the free software QGIS which offers sufficient flexibility and capabilities to realise all data manipulations. All codes were implemented using the Python programming language and the Scikit-learn library.

The data is tested and validated by splitting it to 70% for training, 15% for testing, and 15% for validation. The metrics used to assess the validation of the model are accuracy, precision, recall, confusion matrix, and under-area curve (Table 2 for mine area predictions). As shown, these models gave good accuracy for the mined area prediction, as well as for other metrics (i.e. recall, precision, AUC). This means that the increase in the sample number and the inclusion of military expertise enhanced the model performance. Note that the RF model gave the best metrics, while XGBoost was the fastest and SVM the most time-consuming algorithm.

Cross-validation is used to tackle the performance on unseen data. Table 3 shows the confusion matrices relative to five folds used in cross-validation, where the maximum and minimum accuracy obtained were as follows: max accuracy = 97.47%, min accuracy = 97.29%.

Table 4 shows the results of the test and validation datasets for the RF classifier, whose figures are almost equal and above 97% which indicates that

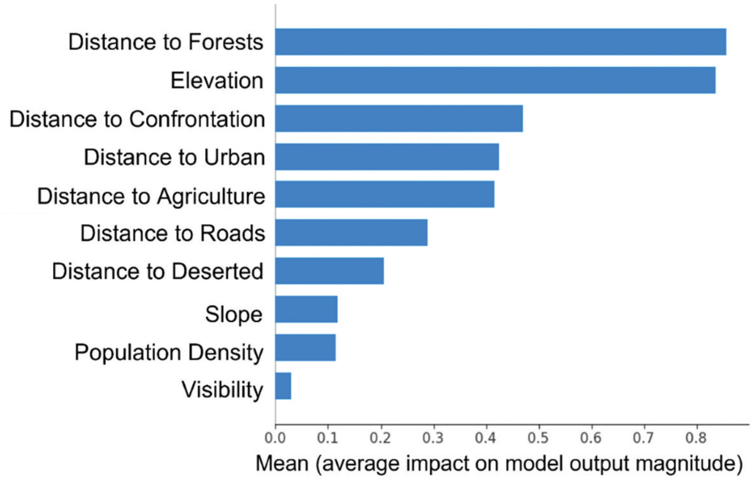


Figure 7. Shapley values, RF classifier.

our model is performing well. Ablation tests have been performed and inserted in section 5. It appears that even though visibility and confrontation lines are binary variables, their influence on the computation experiments is minor as ablation results showed a decrease in accuracy by 2% as shown in Table 5. On the other hand, the role of those two added variables is essential from a military perspective, as they ensure the selection of an appropriate region where mines are supposed to be planted and eliminate the risk of selecting non-relevant data. In fact, if the study area is not properly selected, the study zone is too large and filled with parts unsuitable for mining, making the problem highly imbalanced.

Figures 8 and 9 are also generated by QGIS and show the prediction results for the splits (10×10 m) chosen by the RF algorithm for testing (i.e. for the combination 70/30, where 30% of the samples were chosen for testing and 70% for training), in different areas (South Lebanon and North Lebanon), and it appears that this model converges well in predicting mined areas within relatively small areas.

Military demining experts follow a methodical way to classify minefields by priority of clearance depending on their socio-economic impact, i.e. the most the mined area is susceptible to be accessed by people, the more it became important to clear it first, and thus will be classed as a priority for clearance. Those experts also classify the minefields by difficulty of clearance due to their altitude (relative to sea level) where the weather constraints took place, and also due to the slope of the terrain which makes them easy or hard to work in. After identifying the mined areas, they can be classified by priority of clearance. The Random Forest (RF) model (BalancedRandomForest) is used as it gave the best

Table 2. Results for mined area prediction.

	Accuracy	Precision	Recall	AUC	Execution time(s)
SVM	0.955	.978	0.93	0.955	14350
RF	0.975	.962	0.976	0.975	7207
XGBoost	0.941	.906	0.947	0.942	59

Table 3. Confusion matrices for five folds (cross-validation).

[[40834 784]	[[40847 771]	[[40919 698]	[[40913 704]	[[40888 729]
[808 16,267]]	[750 16,325]]	[789 16,287]]	[820 16,255]]	[787 16,288]]
Fold 1	**Fold 2**	**Fold 3**	**Fold 4**	**Fold 5**

Table 4. Accuracy of test and validation datasets, RF classifier.

Dataset	Accuracy %
Test	97.15
Validation	97.19

Table 5. Ablation test.

Ablation test	Accuracy %
All Features	97.47
Without Military Features	95.91

accuracy results in the previous step. The results were 99.07% for all the metrics used (i.e. accuracy, precision, and recall) compared to the classification made by military demining experts. The last phase is the classification of mined areas by difficulty of clearance. The RF model is also used, and the results were also 99.03% for all the metrics used (also compared to the classification made by military experts). Note that the results were high (99%) because the boundaries separating the priority and difficulty classes are clear and well defined as ranges of values, and the result of different features is well known. For instance, for the difficulty class, the variables used were elevation and slope and were split into ranges (i.e. 0 to 500, 500 to 2500, and >2500 for elevation, 0 to 15, 15 to 30, and >30 for slope) which makes it easy to correctly classify within these ranges.

Figure 10 shows the predictions for priority in an area close to urban agglomerations, and the results gave high priority, and Figure 11 shows the low priority predictions in a deserted area where human access frequency is very low.

Figure 12 shows the area predicted as easy for the difficulty class in a plane land, and Figure 13 reveals the variation of difficulties from hard to easy with the slope variation, where the lighter areas stand for a higher slope and the

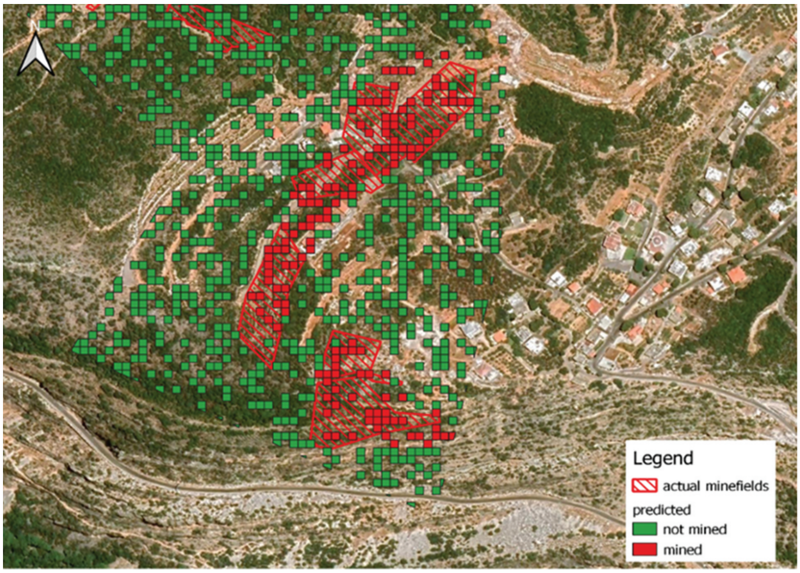


Figure 8. Predictions for mined areas in South Lebanon.

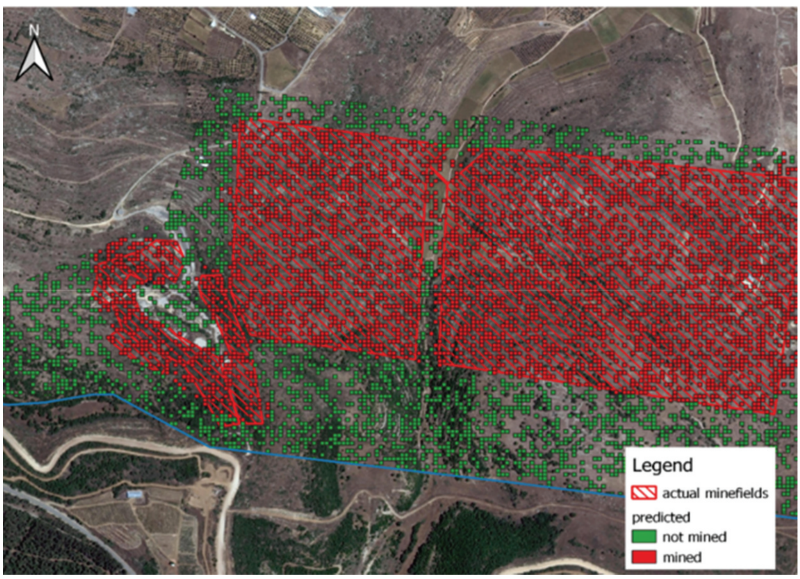


Figure 9. Predictions for mined areas in North Lebanon.

darker areas stand for plane land (low slope). As noticed in Figure 13, there is some heterogeneity in the 10×10 pixels classification for difficulty, this is related to the high resolution of the DSM used to generate the slope, where small variances in slope are recorded, and the final interpretation would be done by the military demining expert to assess the difficulty of the entire area. Figures 10-13 are generated by QGIS.

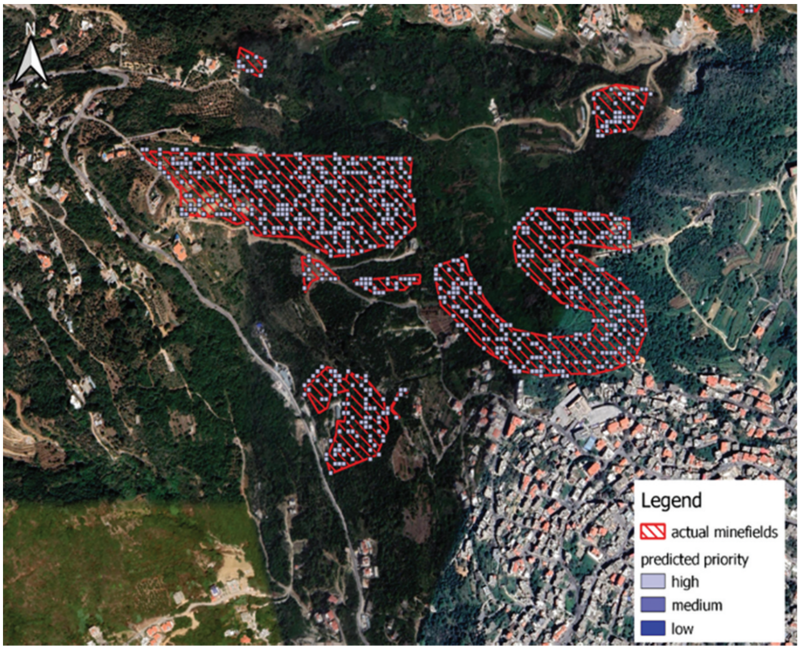


Figure 10. High-priority prediction in urban areas.

As can be observed, the accuracy results of our model are very good, but there is something to emphasise: the objective is to predict mined areas, i.e. the areas favourable to plant mines in, not the exact location of each mine. This can be later done by demining experts who have the human knowledge and the specialised equipment to do so and demine precisely those predicted areas.

Finally, this modelling framework delivers to the military experts in charge of the demining system, as a service, well-defined vector data (location-based) covering the areas predicted as mined, with the context of their prioritisation and the relative difficulty of clearance, giving them a good starting point for the demining process. This facilitates clearance of the mined areas with high priority and less difficulty, while all areas can be covered progressively.

6. Conclusion and further work

This research highlights the potential of using GIS, ML techniques, and human knowledge in predicting and classifying landmine locations by priority and difficulty of clearance, to improve the efficiency and safety of in situ landmine clearance operations. One of the challenges in this field is that landmines are rare events, making it difficult to collect sufficient data to train an ML model.

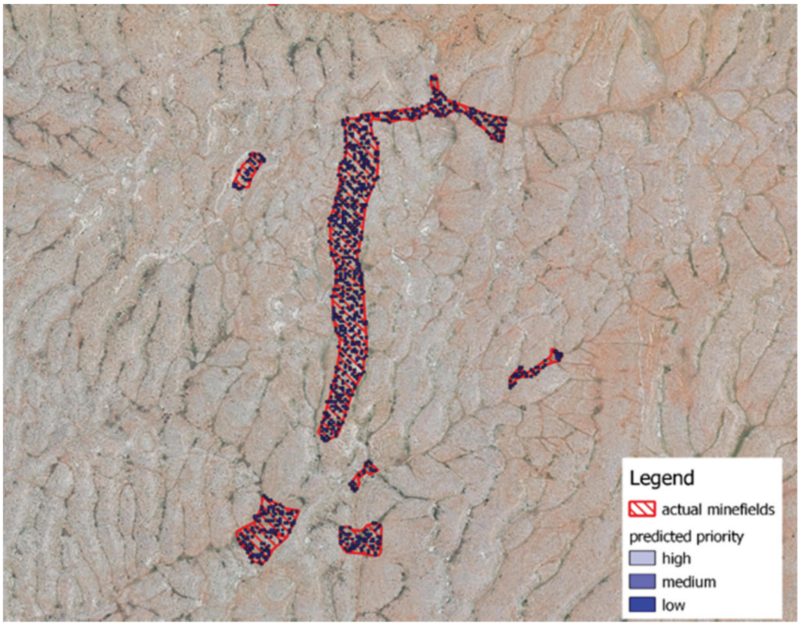


Figure 11. Low-priority predictions in deserted areas.

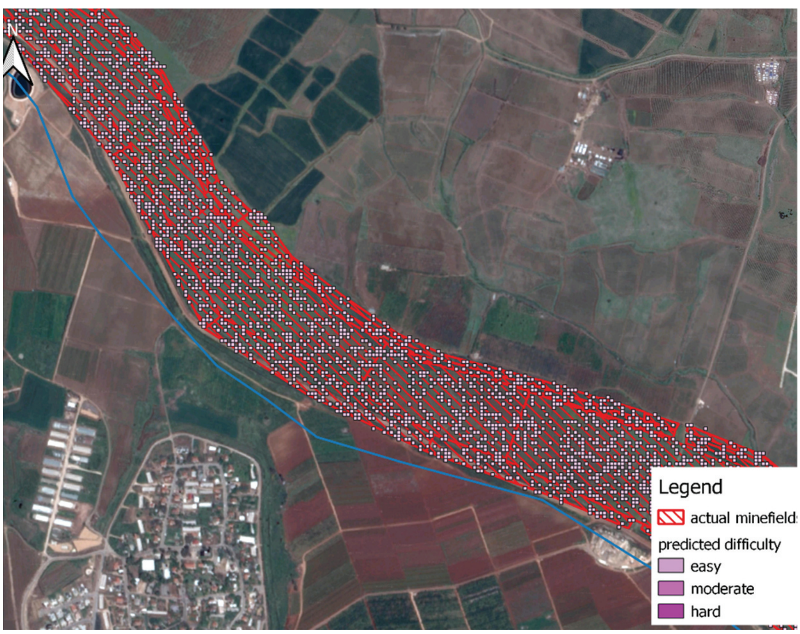


Figure 12. Easy difficulty predictions in plane areas.

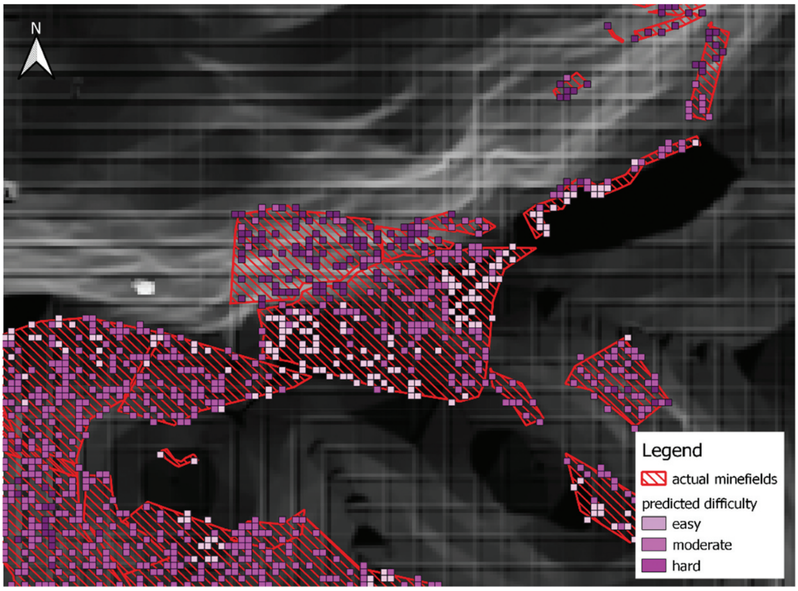


Figure 13. Mixed difficulties predictions varying with slope.

However, the paper suggests that by combining machine learning techniques with military expertise, accurate predictions can be made.

By using their knowledge of landmine deployment and terrain properties, military experts can help to geographically identify areas that are more likely to contain landmines, and they can also refactor the data in a context-aware system capable of delivering further classifications related to priorities and difficulties of the location-based demining tasks. The availability of data is also an important factor, and the researchers note that increasing the number of training samples can lead to increased accuracy. The results of the study are promising, and the integration of military expertise is seen as particularly valuable.

Our model can be applied in real situations by military experts who have to first study the area of operations (i.e. observation and military posts, confrontation lines, 3D aspects of the terrain, the visibility from observation posts, population, and land use), then select the area susceptible to be mined, divide it to small samples, fill in the different features (variables), and finally apply the prediction model.

Future work in this field could focus on differentiating between types of mines, such as anti-personnel or anti-tank mines, depending on the purpose of use which might be defined again by military experts, as different mine types demand different clearance approaches. This would allow for more targeted demining efforts, as different types of mines require different resources and approaches, thus allocating the right resources for demining.

Overall, this research suggests that the combination of machine learning and military expertise has the potential to greatly improve landmine clearance operations and could ultimately save lives and improve the safety of communities affected by landmines.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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