Applying Multiple Deep Learning Models for Antipersonal Landmines Recognition

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Abstract— **Antipersonnel landmines represent a very serious hazard endangering the lives of many people living in armed conflict counties. The huge amount of human lives lost due to this phenomenon has been a strong motivation for this research. Deep Learning (DL) is considered a very useful tool in object detection, image classification, face recognition and other computer vision activities. This paper focuses on DL for the problem of landmines recognition in order to identify it's type based on shape features. This research work consists of several stages: gathering a new dataset of Anti-Personnel Mines (APMs) images for training and testing purposes, employing several augmentation strategies to boost the diversity of training data, applying four different Convolutional Neural Network (CNN) models namely VGG, ResNet, MiniGoogleNet and MobileNet, and evaluating their performances on APMs recognition. In conclusion, results indicate that MiniGoogleNet exceed all of other three models in recognizing APMs with the highest accuracy rate of 97%.**

Keywords— Deep learning, image recognition, landmines, data augmentation, VGG, Resnet, MiniGoogleNet, MobileNet.

I. Introduction

A landmine is an explosive object deployed to destroy or disable enemies. Landmines are implanted during war times hidden under or on the surface of ground and may remain undetected. The existence of explosive remnants of war (ERW), and specifically antipersonnel landmines, are considered as a serious threat for civilians as well as militaries around the World [1]. Many countries have suffered from mining for the last seven decades [2]. According to the UN Mine Action Service (UNMAS) regarding Libya, it has been reported that 108 were killed and another 161 were injured in 135 accidents since March 2011 [3]. The UN Department of Humanitarian Affairs (UNDHA) set a group of strict legislations that determine the strategy of civil area demining. Never-the-less, there is no accurate estimation of these areas which were trapped by landmines. In fact, in order to consider an area free-mining, 99.6% of remnants of war must be safely eliminated. Generally, landmines detection, localization, and recognition are the steps followed by most landmine clearness systems. In reality, most of these systems depend on metal detectors and on deminer experience. Thus, with the purpose of protecting the lives of civilians and militaries, and facilitating demining operations, this paper focuses on the recognition problem which is essential to determine whether an object is an APM or not, and specify its model type [4].

Deep learning is part of Machine Learning (ML) that deals with considerable quantities of data. Recently, the technology of DL has achieved great successes in object detection, image classification, face identification and other computer vision tasks. In fact, many supervised and unsupervised learning tasks were solved using multiple level model architectures [5] [6]. DL uses multiple layers represented in the CNN to generate computational models. The importance of classification derived from the variety of its uses in practical applications such as recognizing images of skin cancer, application of high-resolution imagery to identify disasters like floods, volcanoes, and droughts. Such use of DL will help noting the impacts and caused damages [7] [8].

This paper reports on a study applying four different architectures of deep learning modules for anti-personnel landmines recognition. The authors' motivation for using CNN comes from recent studies [9] [10] indicated that these DL architectures achieve a terrific success for several computer vision tasks such as image segmentation and identification. An important aim of this on going work is to find the most suitable model that allows landmine recognition with respectable accuracy. VGG, ResNet, MiniGoogleNet and MobileNet architectures, consisting of 16, 50, 75 and 28 layers respectively are employed for several experiments. A new dataset of landmine images, consists of 855 images, is used. This research consists of several stages: data collection, data augmentation, training of deep learning models, selection, and comparison. The paper has is structured with eight sections. Section I gives an introduction to the presented topic. That will be followed by section II which gives brief background on mines, deep learning and image recognition. Section III presents an overview of related work. Then, a description of the methodology is reported in section IV. The detailed description of the experiments setup and dataset is reported in Section V. Where the results are described in Section VI, Section VII evaluate the results. The final section VII presents the conclusions as well as the future work.

II. Background

A. Landmines

Mines came from the Latin word "mina" which means vein of ore which is an expression for digging a hole in the ground. Military engineers later used the term in relation with their job of digging landmines in the ground during military operations. At first, mines were applied to destroy goals were placed on earth, but afterwards, these mines were filled with explosive like gunpowder or black powder to cause greater damaged. Mines only began to appear on a large scale in 1918 in which mines against tanks first produced. They could be found along roads, in fields and forest, near wells and river bank causing serious economic problem for the countries. It was estimated that for every 5000 mines that are removed, one person is killed and two persons are injured. A variety of methods are used for the detection of landmines: Metal detector methods, Biological methods and Mechanical methods. With reference to the metal detector methods, sensors are used to measure the disturbances of the released electromagnetic field of metal objects that buried in the ground. Therefore, this method could not be used for plastic landmines. Whilst, the biological method depends on trained dogs, trained bees or bacteria to detect mines covering large areas in short time. The mechanical method relies on clearing paths only using mechanisms such as remote-controlled clearness. Never the less, these methods are considered to be slow, expensive and dangerous [11]. Generally, landmines can be classified in to two types, APM and Anti-Tank mines (ATM).

B. Deep learning

Recently, artificial intelligence (AI) techniques such as ML and DL is being the focus of numerous interesting articles. Whilst AI was born in 1950, questioning computer scientists whether computers should think; machine learning came up with more specific question of whether a computer could accomplish a task without human inter. In order to obtain answers, set of rules and data should be applied by the machine learning. At first, producing rules using data and answers. Then these roles should be applied on new sort of data in order to produce answers for new questions. On the whole, ML systems are to be trained with expels linked to the area of a study with the intention of gaining rules to automate similar studies [13]

Currently, Deep Learning is the tendency in analyzing big data, and in learning systems. As an important area of machine learning that accomplishes classification tasks straight from images, video, texts or sounds, DL is described as a major enhancement of the Artificial Neural Networks (ANN). DL model architectures are consisting of a considerable number of neuron layers that give a superior level of abstraction and progression to the target data. Therefore, deep learning is count as the key automatic learning technique in computer vision and image processing fields [14]. Some of the advanced models of deep learning include AlexNet, VGG net, GoogleNet, ResNet from, and YOLO (You Only Look Once) [15].CNN plays an important role mostly in analyzing visual data items. Although CNN was born in 1980s, it became a breakthrough in 2000 due to acceptance of GPU [16]. CNNs contain higher number of layers compared to the conventional NN, where each layer is trained for identifying certain features in an image. CNNs excel in maintaining spatial relationships with filtered input images. Such relationships are vital for realizing the variations between input image segments. Practically, filters are used in every training image with different resolutions in order to produce output that serves as input to the adjacent layer. At first, the filters produce simple features identifying edges, corners and lines. Afterwards, they generate more complex features that recognize the object [17]. A CNN architecture consists of a number of layers, which include a convolutional layer, a pooling layer, a ReLU layer, a fully connected layer, and a loss layer. Where the main layer is considered to be the Convolutional layer, that is due to the fact that it composed of kernel filters. The filters are to identify target image features, and the pooling layer is used to decrease the number of parameters in the NN. The ReLu layer represents the activation function that is used to set any negative weight values to the zero. The fully connected layer smoothens the output features. Finally, Loss layer illustrates the differences between the predicted labels and the actual values [13].

III. Related Work

For demining purposes, a number of methods have been designed and developed. Conditions such as the type of the buried landmine, the substance of explosion and the nature of soil, determines the used method. In general, most of these detection methods are made of three main components; for capturing signs, a sensor is found; an image processor for handling the obtained signals; and for landmine recognition, a component of decision making is used [18]. Several studies focused on landmine detection rather than recognition. The authors of [19] proved that the standard deep learning techniques can be applied for automating image recognition of landmines. Furthermore, the study [20] proposed and assessed algorithms with the purpose of tackling the problem of detection and identification of landmines using GPRs. Genc and Akar [21] classified the techniques for buried target detection into four categories: shape-based, physics-based, and image-based techniques, and convolutional neural networks (CNNs). While the shape-based techniques are characterized by their ease, they are based on the hyperbola-like shape in B-scan image of ground penetrating radar (GPR) data. Hough transform [22] and alternative fitting techniques [23] are the most recognized shape-based object detection algorithms in GPR data. While Physics-based techniques attempt to assess the core properties of the buried object using its shape and size [24]. However, this technique is likely to fail as a result of the unidentified environment that the object is buried in [25]. Another well-known GPR-based landmine identification method is Image-based technique where features are extracted from B-scan image of GPR data in order to determine whether the buried object is threat or not [26-30]. Yet computational complexity is an obstacle [31][32]. While the three previous techniques rely on the separation between feature extraction and classification phases, the literature review shows that CNNs can deal with both phases cooperatively. As a matter of fact, landmine detection using CNNs in GPR B-scan data has been explored in several prior studies. CNNs results depends on the availability of a sufficient amount of data such as different landmines in various environments. However, as a large amount of existing GPR data of landmines is owned by military, it is hard to collects sufficient data to train CNNs [33-35].

IV. METHODOLOGY

A. *Dataset and Preprocessing*

A set of 855 samples of Landmines were obtained. The original dataset was collected for training and testing purposes, and it was gathered using one of the following three ways: Firstly, downloading images manually from landmines data websites such as CAT UXO [39]. This way consumed a lot of time simply due to the amount of human work involved. Secondly, using an automated python script works to download landmine images from the internet, which helped gathering images faster and with less effort. Finally, a few images were captured from real field in Libya using a mobile phone. The dataset is divided into 7 classes of Landmines images which are named according to the shape as, Butterfly Shape, Cylindrical Fan Around, Cylindrical Flat, Cylindrical Upper Bump, Cylindrical Upper Fan, Screw Shape, and Rectangle Shape. Some images are given in Figure 1. Additionally, the size of a training dataset was expanded using data augmentation. Therefore, a new dataset of 7000 samples were generated of augmented images after using data augmentation technique.

Fig 1. Sample examples for each class of Landmines.

The following table summarizes the dataset. approximately 80% of the images in the dataset were in the training set, and 20% were in the validation set.

TABLE I. DATASET DETAILS

No of Class	Classes	Number of images
1	ButterflyShape	1000
2	CylindricalFanAround	1000
3	CylindricalFlat	1000
4	CylindricalUpperBump	1000
5	CylindricalUpperFan	1000
6	ScrewShape1	1000
7	RectangleShape	1000
	Total	7000

B. *Data Augmentation*

In order to build effective Deep Learning models, it is important to keep the validation error as low as possible while keeping the training error to a minimal. The effectiveness of this strategy may be proven by using data augmentation. Image data augmentation includes several techniques used for increasing the size of training datasets and add variety to datasets in order to build more accurate deep learning models. However, modified versions of original images were added into the dataset [40]. It is considered as a powerful technique for improving the accuracy of modern image classifiers [41].

In many machine learning tasks, Data augmentation is a commonly used technique. A variety of augmentation strategies have been proposed and shown to capture important characteristics of natural images. The augmentation strategies can generate variants of the images, which can increase the fit models' capacity to generalize their knowledge to new images.[42]. One of the more effective data augmentations strategies is the traditional transformations, include flipping, Rotations, Zooming, and shifting. To perform the basic transformation, only affine transformations are used [43]. Each input image was output in two distinct forms; an exact copy shifted (width/height), zoomed out, rotated, flipped(horizontal), sheared, or rescaled. Eight augmentation strategies were utilized to generate new training sets. The following Table 2, illustrates the data augmentation techniques used in this experiment for randomly generated images.

TABLE II. AUGMENTATION TECHNIQUES

Technique	**Description**	**Value**
Rotation	Rotational augmentation can be performed by turning the image clockwise (between 1° and 359°) or counterclockwise (between 359° and 1°). Rotate the image between 0 and 40 degrees for the value of 40.	40
Rescale	In scaling or resizing, the image is resized to the given size.	64x64
Shear	Shear the image with increasing rate magnitude along the horizontal (vertical) axis. The value 0.2 meant shearing the image by 0 to 20 degrees.	0.2
Zoom	Zooming is for randomly zooming inside pictures. The value 0.2 means zoom-in and zoom-out by 20%	0.2
Flipping	It is for randomly flipping half of the images. Randomly flip inputs horizontally.	True
Width shift	Shift the image by 20 % along the X-axis.	0.2
Height shift	Shift the image by 20 percentage along the Y-axis.	0.2
Fill mode	Filling the area that was left over of shifting with the nearest pixel and stretching it.	Nearest

To illustrate the effect of augmentation strategies that were used for the purpose of this study, Figure 2, presents a set of the training images before and after augmentation.

Fig 2. Examples of original image vs augmented images

V. EXPERIMENTS

In the experiments, the authors adopted four deep neural network models called VGG, ResNet, Minigooglenet, and MobileNet. These models were trained with a high-performance computing (HPC) unit, which has the following specifications: AMD Ryzen 2600 CPU, 16 GB RAM, and Nvidia GTX 980TI. Data processing and training was carried out using Keras library [44]. This API was built using Python, and runs on TensorFlow.[45]

A. VGGNet Model

The VGG16 CNN architecture, as its name suggests, is made up of 16 layers of neurons. It was proposed in 2014 by Simonyan and Zisserman of the University of Oxford.[46]. The majority of f this network is made up pf convolution and dropout layers. Normalization, concatenations, and shortcuts were excluded. This model achieves an accuracy of 89.88 precent on top-5 test accuracy in ImageNet, which has over 14 million images belonging to 1000 classes[46]. The VGGNet was very straightforward. It contained only three * three convolutional receptive field layers, it was capable of differentiating fundamental directions only. Additionally, it contained three completely connected levels and two pooling layers with a capacity of two.

B. ResNet Model

A residual neural network (ResNet) was launched in 2015 by He et al. [47], ResNet, or Residual Network trains Convolutional Neural Networks to previously unthinkable depths by utilizing what is known as a residual module. and can gain accuracy from this increased depth. With Resnet, networks with more than 100 layers may be effectively trained on the difficult ImageNet dataset. ResNets divide convolutional layers into Residual Blocks, and each block is given a Residual Connection by passing the corresponding block. the residual block's output is merged by summation with the original input that was forwarded by the residual connection. Eight times as deep as VGG nets, residual nets with a depth of up to 152 layers were tested on the ImageNet dataset. ResNet's depth was 20 times that of AlexNet. In our experiments a ResNet of 50 layer depth was adopted

C. MiniGoogleNet Model

MiniGoogleNet, as suggested by its name, it is a smaller version of GoogleNet model. It has simpler architecture complexity, and it was explored as logo detector to decrease the number of model parameters and the workload associated with training. The MiniGoogleNet architecture is built on three main modules: First, there is a Conv Module that is responsible for convolution, followed by Batch Normalization and ultimately, activation. Second, Inception Module which is like a two-branched mini-inception module, one is module that learns 1×1 filters, as well as the other one is also a Conv Module that learns 3×3 filters. Third, Downsample Module, which is responsible for decreasing an input volume's spatial dimensions. MiniGoogleNet was tested using three open datasets. The model achieves 90% accuracy on CIFAR-10 [48].

D. MobileNet Model

MobileNet model is built on a simplified design that It utilizes depthwise separable convolutions to construct lightweight deep neural networks. The model introduces 2 global hyper-parameters which make an effective trade-off between latency and accuracy. Depthwise Separable Convolution is a core layer of MobileNet [49], Which is a type of factorized convolution in which a conventional convolution is factorized into a depthwise and pointwise convolution. In the first convolution, Each input channel receives a single filter. The second convolution then uses one * one convolution to combine the depthwise convolution outputs [50]. the first layer, which constitutes a complete convolution, the MobileNet has 28 layers. In ImageNet, the model obtains an accuracy of 0.895 percent for top-5 tests[49].

To summarize, the following Table 3, indicates a comparison between VGG, Resnet, MiniGoogleNet and MobileNet models. ResNet exhibits one of the highest performance accuracies in the ILSVRC 2012 dataset, outperforming VGG and GoogleNet.

TABLE III. COMPARISON MODELS

	Models			
	VGG	**ResNet**	**MiniGoogleNet**	**MobileNet**
Published	2014	2015	2016	2017
Size	528MB	98MB	20MB	25MB
Top-5 accuracy	0.901	0.921	0.900	0.895
Parameters	138,357,544	25,636,712	1,662,295	4,253,864
Layers	16	50	75	28
Default input size	224x224	224x224	224x224	224x224

These pretrained models can be evaluating using various metrics, such as Recall, F Score, precision and accuracy. However, the final results are based on accuracy. Precision is a term that refers to the proportion of Predicted Positive situations that are in fact Real Positives. It could be defined as the proportion of correct positive results to the proportion of anticipated positive results by the classifier.[51]. Conversely, Recall or sensitivity refers to the proportion of True Positive cases that are successfully predicted as True Positive. By the +P (Predicted Positive) rule, the Coverage of Genuine Positive instances is measured. to sum, Recall is defined as the proportion of correct positive outcomes to the total number of relevant samples. while the F1-score is the arithmetic mean of Precision and Recall. Accuracy is defined as the ratio of correct predictions to total input samples. Commonly, accuracy is the most applied metric to evaluate the model performance [51].

In our experiments, The Four models were setup to be experimented on the landmine's dataset. When the data and labels are loaded to the model, training and testing split are performed, 75 percentage of the data is used for training, while the remaining 25 percentage is used for testing. Our images were preprocessed before they were fed to the models; every image in our dataset was resized to 64×64 pixels. Once the image is resized, it is scaled to the range [0,1]. In the all experiments, The cross-entropy [52] is applied as our loss function, and as our optimizer, stochastic gradient descent is used with a learning rate of 0.005. All models were trained for 150 epochs using mini-batch sizes of 32.

VI. Results

Examining this figure 3, we can see that MiniGoogleNet is obtaining 99% training accuracy. Furthermore, looking at our accuracy and loss plot over time in the figure demonstrates that our network is behaving quite well, after only 20 epochs the network is already reaching ≈ 99% classification accuracy. Loss on both the training and validation data continues to fall with only a handful of minor "spikes" due to our learning rate staying constant and not decaying. At the end of the 40th epoch, we are reaching 99% training accuracy on our training set.

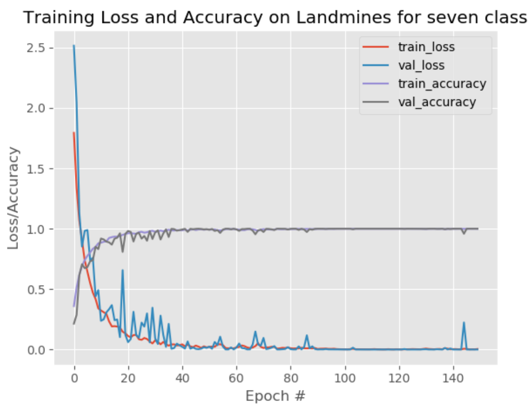

Fig3. MiniGoogleNet's result on Landmines dataset

The above plot shows a quintessential graph as the loss decreases each time the accuracy increases, moreover the training and validation loss and accuracy mimic each other indicating that our network is learning the underlying patterns without overfitting. In addition, the result illustrates in Figure 4 shows that after only 50 epochs the MobileNet model achieved an overall accuracy of ≈ 99% training accuracy.

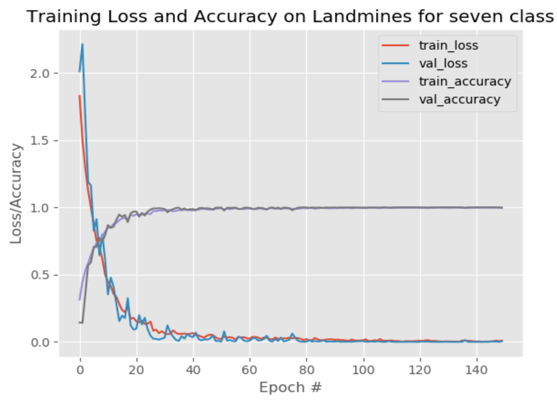

Fig4. MobileNet's result on Landmines dataset

As well as, the result illustrates in Figure 5 shows that after only 20 epochs the ResNet model achieved an overall accuracy of ≈ 99% training accuracy.

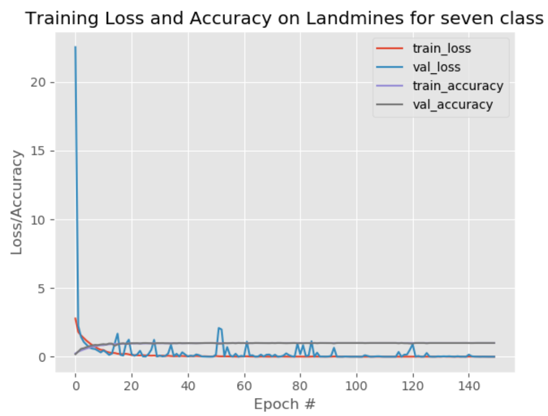

Fig5. ResNet's result on Landmines dataset

Furthermore, the result illustrates in Figure 6 shows that after only 60 epochs the VGG model achieved an overall accuracy of ≈ 99% training accuracy.

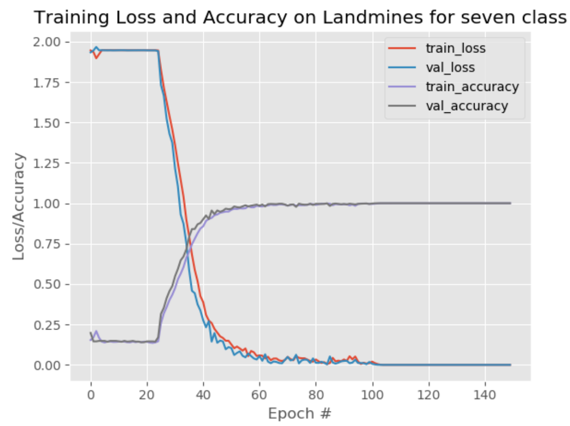

Fig6. VGG's result on Landmines dataset

The models' performance was determined by the ability to predict the correct landmines type on 1750 testing images. The best performing model is MiniGooglenet which achieves a mean F1 score of 0.9714, an overall accuracy of 97.0%. The experiments' results are tabulated below in table 4, it is apparent that all of the models showed a different performance.

TABLE V. COMPARISON BETWEEN RESNET, VGG, MOBILENET, AND MINIGOOGLENET

Performance Measures	VGG	ResNet	MinigoogleNet	MobileNet
Precision	59.42	85.57	97.42	85.42
Recall	59.71	86.00	97.42	85.85
F-Score	59.42	85.71	97.14	85.42
Accuracy	**60.00**	**86.00**	**97.00**	**86.00**

Starting with the Precision, VGG had the lower results with 59.42%, followed by MobileNet with 85.42%, ResNet 50 with 85.57%, and the best Precision result with MiniGoogleNet, which obtained 97.42%. In the same way, the order of the Recall results was equal to the previous measure, where the lower percentage was obtained by VGG 59.71%, and the highest by MiniGoogleNet with 97.42%. On the other hand, F-score measurements, VGG achieved lower result with 59.42%, followed by MobileNet, ResNet, and MiniGoogleNet with 85.42%, 85.71%, and 97.14% respectively. Finally, in the accuracy metric VGG performance was poor with 60.0%, followed by MobileNet, ResNet which are showed a similar result with 86.0%, and highest result was obtained by MiniGoogleNet with 97.0%. Indeed, as is shown, the MiniGoogleNet implementation achieved the highest percentage.

VII. DISCUSSION

Deep Learning provides a good opportunity to expand a research and the application of the basis for Landmine classification using digital images. The accurate models presented by deep learning are required to recognize the landmines. For this work, four models, namely VGG, Resnet, MiniGoogleNet, and MobileNet were trained. As well as, the dataset used provides seven classes of the landmines, which have a total of 6995 images. the dataset was extended using data augmentation techniques. The dataset was allocated 75% to training, and 25 percent for testing. As observed in the results section, All of CNN models were evaluated by various metrics: precision, Recall, F-Score, and accuracy, using the same epochs. Based on Table 4, which shows a general result performance, MiniGoogleNet achieved better results than the other model architectures. Both neural networks, ResNet and MobileNet were had Converging result. On the other hand, VGG shows lower performance. Additionally, although all models were trained using an equal number of epochs at 150, it can be noted that the training process can be stopped early without affecting the accuracy rate. However, based on the results of the experiment on models, the accuracy was starting to be stabilized at 40 epochs in MinigoogleNet, MobileNet, and ResNet, as indicated in Figures 3, 4, and 5, respectively. Correspondingly, as shown in Figure 6, VGG model recorded that the accuracy stops keeping grow up at 60 epochs, which mean that the network accuracy starts saturating. In fact, this pointed that the training process can be safely stop at a smaller number of 150 in our experiments

To sum up, this paper showed that deep learning models were feasible and beneficial in antipersonnel landmine recognition. In addition, it could be beneficial to create a landmine recognition mobile system that implements the best model for recognition of Antipersonnel Landmines, MiniGoogleNet is a good recommendation predictor for building a mobile application, so users with a little or no knowledge can use it to recognize of Landmines.

VIII. CONCLUSTION

This paper demonstrated the usage for models of deep learning in a new application of landmines recognition. In recent years, deep learning technologies in image recognition has accomplished great successes. For the purposes of this paper, CNN four different models were used to verify the classes of the proposed dataset. A new APMs dataset was collected as part of this ongoing research. In order to expand the training dataset, traditional data augmentation methods - based on a mixture of affine image transformations are fast and simple to apply were adapted and have shown that data augmentation is the most often used technique for decreasing overfitting and increasing the dataset size. The CNN models MiniGooglenet, ResNet, MobileNet, and VGG were used to recognize APMs. The findings of the experiments reveal that three models achieve a good level of accuracy between 86% and 97%, on 1750 test images while last model achieves poor result. In fact, MiniGooglenet seems to be the valuable choice for this experiment with the best results on landmine dataset. To conclude, it has been demonstrated that convolutional neural networks provide excellent results in image recognition. For upcoming work, our future goal, therefore, is to improve our current landmine dataset by increasing the number and the diversify of its images is a long-term plan. Experiments on different models and comparing them are another objective. In the near future, the main goal is employing the chosen DL Model and the generated dataset to develop an APM recognition mobile application. That would be a great assistance for dominer in landmine fields.

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