**Algorithms for Intelligent Systems**
*Series Editors:* Jagdish Chand Bansal · Kusum Deep · Atulya K. Nagar

Satyasai Jagannath Nanda
Himanshu Mittal
Meng-Hiot Lim *Editors*

# Proceedings of International Conference on Paradigms of Communication, Computing and Data Analytics

PCCDA 2025, Volume 1

Springer

# Algorithms for Intelligent Systems

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Satyasai Jagannath Nanda · Himanshu Mittal ·
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Editors

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# Preface

This book contains outstanding research papers from the 5th International Conference on Paradigms of Communication, Computing and Data Analytics (PCCDA 2025) organized by Pt. Lalit Mohan Sharma Campus, Rishikesh, Sri Dev Suman Uttarakhand University, Uttarakhand, India, and technically sponsored by Soft Computing Research Society, India. The conference was conceived as a platform for disseminating and exchanging ideas, concepts, and results of the researchers from academia and industry to develop a comprehensive understanding of the challenges of the advancements in communication, computing, and data analytics and innovative solutions for current challenges in engineering and technology viewpoints. This book will help strengthen the affable networking between academia and industry. The conference focused on machine learning, deep learning algorithms, models, and their applications.

We have tried our best to enrich the quality of the PCCDA 2025 through a stringent and careful peer-review process. PCCDA 2025 received many technical contributed articles from distinguished participants from home and abroad. PCCDA 2025 received 443 research submissions. After a very stringent peer-reviewing process, only 47 high-quality papers were finally accepted for presentation and the final proceedings.

This book presents the first volume of 24 research papers on communication, computing, and data analytics and serves as reference material for advanced research.

New Delhi, India — Himanshu Mittal
Jaipur, India — Satyasai Jagannath Nanda
Singapore — Meng-Hiot Lim

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# Chapter 17
# Buried Landmine Detection Using Deep Convolutional Neural Networks

**R. S. Ponmagal, V. Srividhya, Sujatha Kesavan, G. Vijaya Gowri, N. P. G. Bhavani, and U. Janaki**

## 1 Introduction

The global rise in terrorism increases on a daily basis, despite the advancements in government measures for combating terrorists. This has posed a serious threat to the government and civilians. The development of more security systems is required to curb this menace. The use of weapons by terrorists has a significant impact on the public, psychological effects, and economic costs of society. Thousands of people die annually as a result of terrorist's violence. It is affirmed that children that are exposed to high levels of terrorism in their communities usually face a high level of psychological trauma [1]. Children that witness terrorist activities or those that become victims can experience negative psychological effects for a very long time. There are two different types of weapons: the primary weapon and the secondary weapon. Studies show that handheld guns and knives are the primary weapons mostly

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used by terrorists for their nefarious activities. These tools are normally hidden by these terrorists whenever they want to carry out their operation until they get to their target. On this note, these researchers want to develop a model that can identify these disruptive tools in humans, monitor any suspicious activities, and report the same to law enforcement agencies for further necessary actions [2].

The use of landmines such as improvised explosive devices (IED), guns, and knives has been a major threat to Nigerians for the past decade, which has involved a series of attacks by Nigerian terror organizations that make use of these dangerous weapons for their nefarious activities [3]. Unique among its sort occurred in Nigeria in 1986 when a letter bomb was sent to Dele Giwa in his house, which led to his untimely death [4]. Nothing of the sort was heard until 2011, when a series of blasts occurred at the UN headquarters in Abuja that claimed many lives and destroyed lots of properties [5]. These incidences have been occurring since then at different places, such as markets, places of worship, bus stops, and campuses, where many people are involved [6]. The most advanced and dangerous new bombs use mobile phones to enable terrorists to set off a device immediately [7]. This arose with the development of weapon detection using CNN. The key contribution is to detect the buried landmine using deep convolutional neural networks.

## *1.1 Convolutional Neural Network (CNN)*

An integral part of deep learning that is used for intelligence, processing, accuracy, and data improvement. It is composed of a multi-data processing layer that trains the data representation through an abstraction of the various levels. Convolutional neural network (CNN) is been used in various research studies such as: human pose segmentation, face recognition, image classification, image detection, speech recognition, and so on [8]. CNNs have been found to be more accurate and faster, and it is a combination of layers in which each layer plays a distinct role in the network [9].

## *1.2 Object Detection*

Object detection according to [10] is a term used to describe the process of locating things inside an image. Detection of face, pedestrian detection, and detection of skeleton are some of the most common tasks in object detection. One of the fundamental issues in computer vision is object detection, and it is very useful in providing information for semantic comprehension of images and videos. It is also useful in different applications like image categorization, analysis of human behavior, face recognition, and autonomous driving detection. Object detection can be viewed as a means of finding and classifying objects in an image. This can be approached using deep learning like regions with CNN that combines rectangular region indicting the features. Object detection is the combination of localization and classifications. It uses feature extraction and learning algorithms or models to recognize instances of various category objects [11]. Object detection is the estimation of the class and location of objects contained within an image. It is basically an instance-wise vision task. Prior to the rise of deep learning, object detection in computer vision was accomplished using manually created machine learning features including shift-invariant feature transform, histogram of directed gradients, and many more [12].

Some variables were pointed out by researchers [3] that can be used to identify the terrorists, especially in a gathering. This can be further strengthened by developing a model for detecting such weapons in order to eradicate such a menace in our society. The use of weapons to perform evil acts has been posing a serious threat to Nigerians, as seen during number of attacks by the terrorist. This kind of occurrence claimed numerous lives and left numerous buildings and businesses in ruins for a decade in Nigeria. The deployment of improvised explosive devices, targeted killings, ambushes, drive-by shootings, suicide bombers, and kidnappings are some of the terrorists' tactics that call for urgent attention [13].

### *1.3 Research Motivation*

Insecurity has been a major challenge confronting our societies these days. There are rumors of wars from different quarters of the world almost every day with the use of weapons. This is worrisome and calls for concern. Weapons are harmful objects that are used by some groups of people, most especially terrorists to injure governments, civilians, and the military. Most of these weapon objects are not easily identified by necked eyes. On this basis, there is a need to develop a model that can be used to identify and detect these objects on the human body, especially while in a crowd, to save people from being injured.

### *1.4 Aim and Objectives of the Study*

To develop ResNet50, ResNet10, InceptionV1, and multi-magnification deep residual network (MM-ResNet) models to identify and detect any form (anti-personnel and anti-tank mines) of buried landmines from the aerial infrared imagery captured by the drone.

## 2 Related Works

It is observed that automatic control system should be the primary key for security measure with increased number of criminal activities [1–4]. A model that detects seven different types of weapons using deep learning method were proposed by the researchers. An object detection algorithm [5–8] was proposed by jointing semantic segmentation (SSOD) for images. One of the researchers improved the convolutional pose machines for estimating human pose using image sensor data [9–11]. The goal was to create a new system that uses Google neural network and convolutional pose machines to estimate human position. Few of them worked on the design of a training network based on a convolutional neural network for the classification of objects [12]. The goal was to create a convolutional neural network-based training network and train the picture dataset for object classification in a limited number of class problems. Visible light camera sensors were used for detection of night time images with convolutional neural network-based human detection [13]. The goal was to use a convolutional neural network to detect humans in a range of situations. Fox et al. (2017) [3], worked on the simulation and mathematical modeling for the identification of suicide bombers. The plan was to use radar to find people wearing suicide bomb vests with wires for detonation. Rafi (2016) [9] explored an effective convolutional network for estimating human poses. A network architecture was created with a minimal memory footprint that is effective for estimating human position, and he trained it with components that follow best practices for effective learning. The objective was to learn features at various scales and in various levels. Akcay et al. (2020) used several CNN-driven detection paradigms, including sliding window-based CNN, to work on a convolutional neural network architectures to detect and categorize object within X-ray baggage security footage [2]. In all the literature that was evaluated, no researchers investigated the use of convolutional neural networks to detect hidden objects. Therefore, in order to protect civilians from the threat of insecurity in the society, there is need to identify all instances of weapons on human body, especially when in a crowded setting.

## 3 Methodology

The proposed method was used to detect the landmines using ResNet50, ResNet10, InceptionV1, and MM-ResNet, to find the anti-personnel and anti-tank mines as objects on an image. ResNet50, ResNet10, InceptionV1, and the proposed multi-magnification deep residual network (MM-ResNet) model is a type of deep learning approach that is used to detect various objects on an image. The various CNN models first generate the region of interest. These regions may contain a buried landmine identified using a selective search algorithm. The computation of this algorithm is based on hierarchical grouping of similar regions based on color similarity, fitness, shape, size, and texture.

Color Similarity: This works on grouping the most similarly colored regions as in Eq. 1

$$S_{colour}\left(R_i, R_j\right) = \sum\nolimits_{k=1}^{n} min\left(C_i^k, C_j^k\right) \tag{1}$$

where S is the similarity, and $C_i^k, C_j^k = K^{th}$ the values of histogram bin of region $R_i$ and $R_j$ of the object.

Texture Similarity: This is calculated by generating Gaussian derivatives as in Eq. (2).

$$S_{texture}\left(R_i, R_j\right) = \sum_{(k=1)}^{n} \min\left(t_i^k, t_j^k\right) \tag{2}$$

where : $t_i^k, t_j^k = K^{th}$ are the value of texture histogram bin of region $R_i$ and $R_j$, respectively.

Size Similarity: This makes smaller region merge easily by reducing many bounding boxes to fewer ones that contain objects within the given image.

$$S_{size}\left(R_i, R_j\right) = 1 - \left(\frac{size(R_i) + size\left(R_j\right)}{size(img)}\right) \tag{3}$$

Fit Similarity: This merges different regions that are fit with each other to reduce the number of bounding boxes to fewer ones for easy identification. This is obtained using Eq. (4).

$$S_{fit}\left(R_i, R_j\right) = 1 - \left(\frac{(size\left(BB_{ij}\right) - size(R_i) - size\left(R_j\right))}{size(image)}\right) \tag{4}$$

Equations (1–4) are combined to form Eq. (5). This will be used to determine the presence of an object(s) in the image. This is obtained in Eq. (5).

$$S_{R_iR_j} = a_1 * s_{color}\left(R_i, R_j\right) + a_2 * s_{texture}\left(R_i, R_j\right) + a_3 * s_{size}\left(R_i, R_j\right) + a_4 * s_{fit}\left(R_i, R_j\right) \tag{5}$$

The CNN classifies the cropped and resized regions into weapons and non-weapons. Performance evaluation was measured using detection rate, accuracy, and precision. Detection rate measures the percentage of true targets that is detected. It is obtained using Eq. (6).

$$\text{Detection Rate(DR)} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \tag{6}$$

Accuracy is the measure of the actual performance of the system with regard to both correctly detecting and rejecting targets. It is calculated by the sum of the true positives and the true negatives relative to the total number of GT objects as obtained in Eq. (7).

$$Accuracy(A) = (TP + TN) \Big/ (TP + TN + FP + FN) \tag{7}$$

Precision is the fraction of detected items that are correct. This is obtained in Eq. (8).

$$Precision = TP \Big/ (TP + FP) \tag{8}$$

# 4 Results and Discussion

## 4.1 *Training the Network for Classification*

The datasets were trained for classification. The images were converted to JPG, for the datasets to follow the same format and the datasets were converted to XML file, because the targets were represented as XML files. The target in XML files was converted into strings; "0" to represent anti-personnel mines and 1 to represent anti-tank mines". The RGB format size of the images is 227 × 227 × 3. Same function was developed for the four models used for buried landmine detection. They are the ResNet50, ResNet101, Inception model, and the proposed multi-magnification deep residual network model (MM-ResNet).

## 4.2 *Confusion Matrix for the Models*

Figure 1 denotes the confusion matrix for the various models used for predicting the landmines.

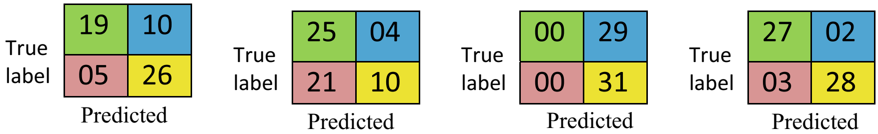


**Fig. 1** Confusion matrix representation. This figure denotes the confusion matrix for the various CNN models denoting the relation between true and predicted classes in determining the hidden landmines. It is matrix representation which deliberates on the performance of the classifier indicating the correct and incorrect predictions

Table1 and Figs. 2 and 3 clearly demonstrated that MM-ResNet has a sensitivity rate of 94%, specificity rate of 91%, and accuracy rate of 93% which were better than the other models like inception model, ResNet50, and ResNet101. The comparison between the models is represented in Fig. 4.

**Table 1** Training results for the ResNet50, ResNet101, Inception, and MM-ResNet

| | RsesNet50 | ResNet101 | Inception | MM-ResNet |
|---|---|---|---|---|
| Sensitivity | 5 | 87 | 66 | 94 |
| Specificity | 10 | 72 | 85 | 91 |
| Accuracy | 53 | 59 | 76 | 93 |
| Loss rate | 4 | 2 | 3 | 1 |

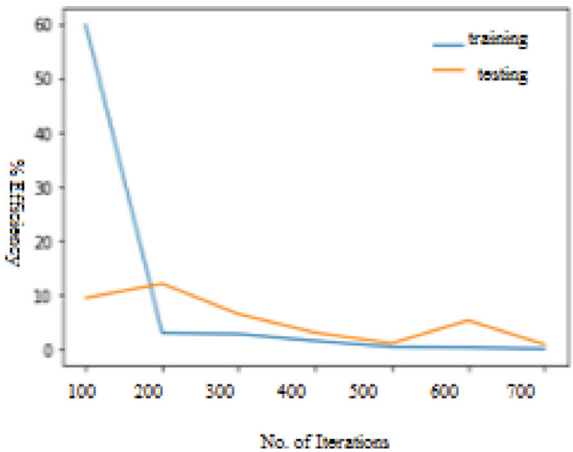


**Fig. 2** Graph for training the deep learning neural network model. Plot for training rate of MM-ResNet-target Vs actual values. This is a graphical illustration where the proposed deep learning models are made to learn the patterns of the input images for classification purpose

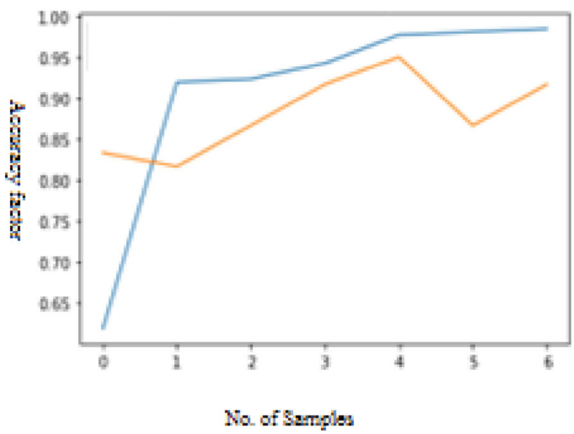


**Fig. 3** Graph for testing the deep learning neural network model. Plot for testing rate of MM-ResNet-target Vs actual values. This is a graphical illustration with which the performance of the proposed deep learning neural network model is tested for obtaining the correct output

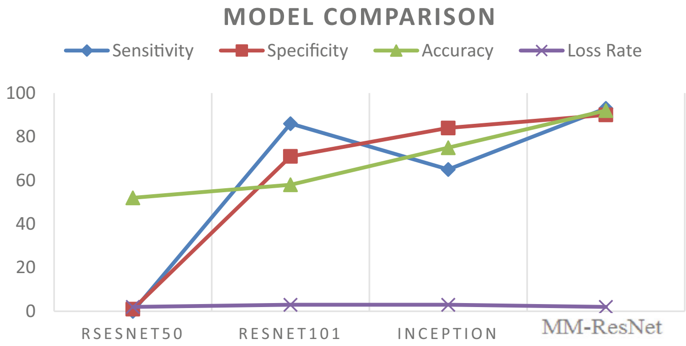


**Fig. 4** Graphical representation for comparison of various DNN models. The ResNet50 and MM-ResNet have the lowest values and highest values for the performance measures, respectively

## 4.3 *Performance Evaluation*

The performance of the MM-ResNet model was evaluated by the prepared test data from images of anti-personnel mines and anti-tank mines captured by the infrared camera mounted on the drone. MM-ResNet, a type of deep learning approach from selective search algorithm, was adopted to test the accuracy of the model. This is shown in Fig. 5. From Fig. 5, a represents the input image, ‘b’ is the extracts series of region proposals from the image, ‘c’ produces warped images, ‘d’ computes feature for each proposal using a convolutional neural network (CNN), and ‘e’ denotes the classified each region into various categories [5].

The weights of the individual neurons were adjusted to extract the right features from the images. This method of adjusting the weights refers to training the neural network. The CNN starts the training with random weights, and the researcher provides the neural network with datasets of images annotated with their corresponding classes. The MM-ResNet compares the output of various images with its

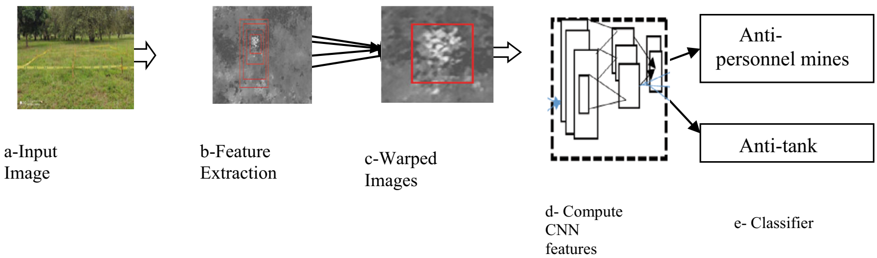


**Fig. 5** Block diagram for detection of landmines using MM-ResNet. From this figure, a represents the input image, ‘b’ is the extracts series of region proposals from the image, ‘c’ produces warped images, ‘d’ computes features for each proposal using a convolutional neural network (CNN), and ‘e’ denotes the classified each region into various categories

correct label assigned with random values after processing. This makes it easier for the network to decide which parts are to be adjusted instead of making random corrections. Each run of the entire training dataset is called an epoch. During training, the MM-ResNet passes through a number of epochs and modifies the weights. The neural network gets a little bit more adopt at categorizing the training images after each epoch. The CNN makes fewer and smaller changes to the weights as it gets better until the network converges. Sufficient datasets are necessary to train sophisticated models, but in this situation, obtaining large datasets for the study was difficult. Datasets were immediately loaded from Google Drive, utilizing the mount drive approach. The runtime instance received a full import of the drive's data. In order to access the datasets, Google Drive was mounted. An image labeler was used to construct the object detection system in a more organized manner. The predicted coordinates were evaluated and contrasted with the actual ground true coordinates in order to evaluate an item detector. In addition to classifying the object in the image, their location within the image was also determined. Some of the objects detected with the developed model and their interval rates. This implies that the developed model can be used to detect an object hidden by a human being.

## 5 Conclusion

Due to the increase in terrorist activities in societies nowadays, it is imperative for individuals, organizations, and the government to devise a means of securing their environment. This study developed a model that identified hidden mines in warfare and classified them as anti-personnel mines or anti-tank mines or non-explosive mines whose images are taken from infrared thermal camera. The essence of this work is to provide a safe and secure military environment during warfare. The limitation of this work is restricted to anti-personnel mines or anti-tank mines only. It can also be recommended that further research is to be carried out on the detection of complex weapons, highly explosive materials and even to nuclear or biological weapons.

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