Novel Buried Threat Detection with Convolution Neural Networks and Recurrent Neural Networks Better Approach

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Abstract

Ground Penetrating Data is a remote geophysical sensory system that has been used intensively and researched. GPR uses radar pulses to image the subsurface and is used to find underground threats and objects. Existing model detectors use specific models or handcrafted features.

To improve on them, algorithms are being evolved to predict the presence of such threats. Through this paper, we propose using vast and authentic GPR data collections and methods driven by discrimination algorithms for BTD's that capitalize on deep convolutional neural networks by combining CNNs and RNNs to investigate two-dimensional ground-penetrating data (GPR) scans in thex-axis and y-axis cartesian directions as well as 3-dimensional GPR volumes.

The data utilizes a vast collection of BEO's including various shapes, metallic substances, and underground internment profundities. We also provide a quantitative analysis that compares the different results found using the algorithms and models on CNN's and conventional learning methods.

In this paper, we compare our proposed method to further the research done on GPR and BEO's by capitalizing on recurrent neural networks and convolutional neural networks to analyze two-dimensional Ground Penetrating Radar B-scans in the x and y axis respectively. We will also analyze three dimensional volumes of Ground Penetrating Radar data.

Keywords: Deep Learning, Ground penetrating radar (GPR), Underground Threat Detection, Combinatory Neural Networks

Introduction

Landmines are instruments capable of massive destruction in slow motion. They do not know the difference between civilians and combatants and contravene international humanitarian law. In recent times, de-mining has received attention and funding worldwide, yet there is no long-term approach to this humanitarian assistance. Every month, eight hundred people are murdered and one thousand and two hundred maimed by land mines. Due to the toy-like shapes and colours, oftentimes, the victims are children. It is estimated that a mishap occurs every twenty minutes.

Machine learning algorithms have been studied for detecting BEO in sensor data for the last two decades. Several of these techniques were refined and integratedfor this particular application.

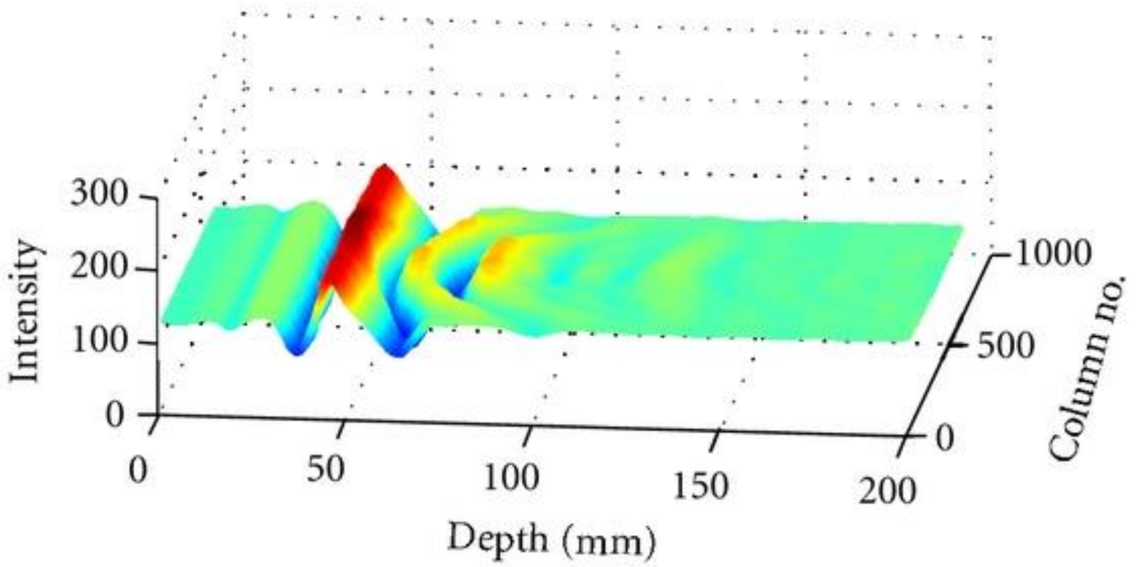
The ground-penetrating radar is a widely used sensor for detecting buried threats. Its ability to detect objects of interest is very effective for buried threat detection (BTD).

The necessary tools required for early detection of these are still not readily available in most populations globally. GPR uses electromagnetic waves in the microwave band (frequency from 1 to 1000 MHz). GPR requires two main components- a receiving antenna and a transmitter. GPR emits a pulse into the ground and records the results (using echoes, as it is a radar) from subsurface objects due to anomalies of dielectric nature (example, an object buried underground). As a result, GPRs detect non-metal objects on the basis of their dielectric contrast with the soil. The GPR system has software that translates these signals into images of objects from the subsystem.

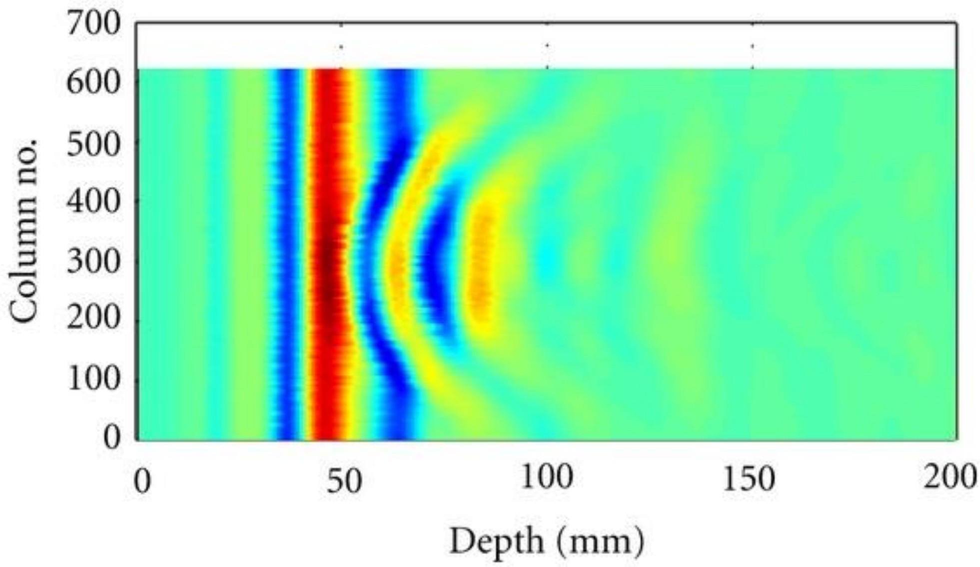
Traditionally, underground threat detection mechanisms follow a multi-step process.

Step one is to compute the flow of data from the GPR and identify areas of possible threats that correspond to points with unique signatures. For this, we use a detector programmed to detect the earlier defined anomalies.

Following that, we use an algorithm based on machine learning (referred to as a classifier) to assign a value telling us with confidence about the unique threat detected is legitimate or a false positive.



(a)



(b)

Fig 1: (a) Front View (b) Top View

Sample raw GPR data

Literature Survey

1) D. Reichman, L.M Collins et al. [1] have put forth the concept of the GPR (Ground Penetrating Radar) Framework which is programmed to detect unique locations of the hidden danger. The radar radio wires have been mounted on the facade of the vehicle, wherein the GPR gathers the information while the vehicle moves ahead. The modernized calculations were used to process the information received. An energy-based pre-screener named F1V4 was specifically employed to collect shape data that prompts the presence of covered danger. Initially, Histogram of Oriented Gradients (HOG) descriptor was used, which exercises both energy and shape data for pre-screening which provided indifferent results.

2) The crude information received from the GPR is re-arranged to measure commotion, surface harshness, certain dirt particles. The aim was to:
i) Identify the subset highlights that influence the objectivesof the given classifier and,
ii)The GPR sensor mounted on the vehicle extracts distinct highlights from foundation districts, the research also includes relapse calculations to acquaint with the model that predicts the PD objectives for a given path (A. Manandhar, L.M. Collins, P.A. Torrione et al.) The consent for our outcomes is done by utilizing distinctive cross-approval strategies.

2) J. M. Malof suggested that the computations for a customized area using GPR assessments can distinguish the hazard. GPR is a well-known, efficient modality to detect Buried Threat Detection (BTD), therefore scrutinizing GPR-based BTD calculations can lead to the advancement of the GPR BTD algorithm framework. Likewise, these also report consequences of assessing calculations obtained from large trial information which sums up to 123,000m squared of GPR information utilizing surface region, from 15 vivid paths across 2 test terminals located in the United States of America.

3) Incorporating Convolutional Neural Network (CNNs) with GPR infiltrating pictures to scan a covered landmine location was proposed by S. Lameri, F. Lombardi, P. Bestagini et al. [4]. The given calculation algorithm is well equipped to provide a B-Scan Profile that hints at the covered landmines through liable GPR acquisitions. Accordingly, 95% of identification precision is quite an attainable result through the stated landmine acquisition profile.

4) L. E. Beesaw and P. J. Stimac [5] communicated that the progress of symmetric and asymmetric buried unsafe hazards (BEHs) still poses a valid threat on the front line. However, the evolution of machine learning furnishes a greater potential for automated threat detection. Recent breakthroughs in artificial neural networks have indicated high performances in pattern recognition tasks, therefore ensuring deep scanning of uncovered danger.

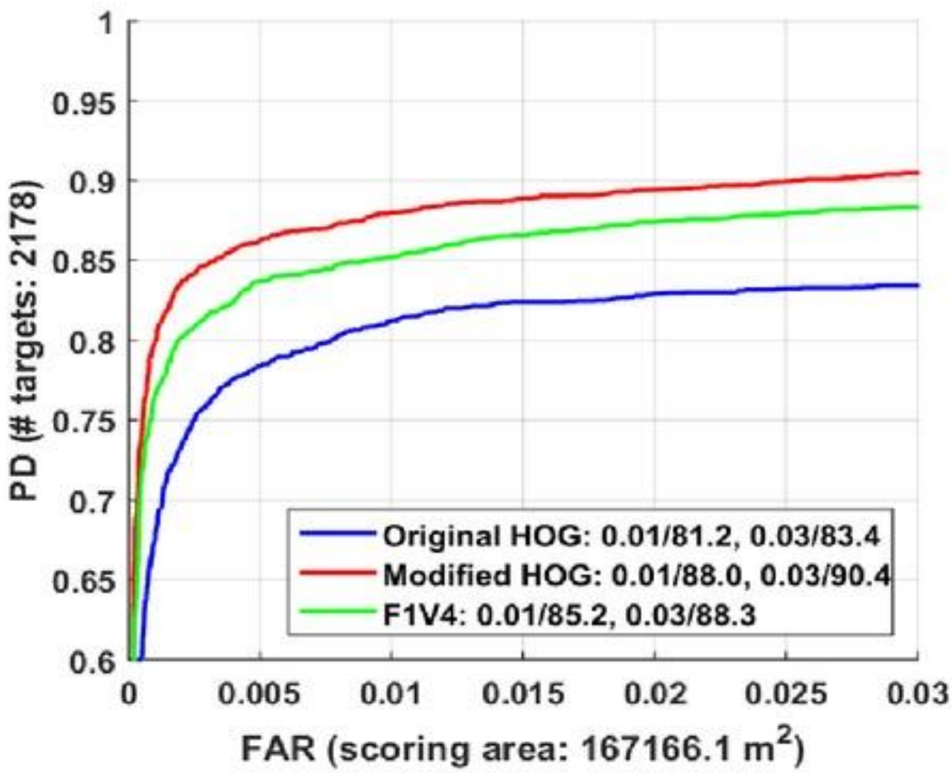


Fig 2: Graph representing the ROCs for the Original HOG prescreener, Modified HOG prescreener and F1V4 prescreener

Background

Deep Learning

Deep learning is a subtype of machine learning that consists of three or more layers of a neural network. These neural networks aim to imitate the activity of the human brain by allowing it to "learn" from enormous amounts of data, albeit they fall far short of its capabilities.

While a single layer neural network can still produce approximate predictions, additional hidden layers can assist optimize and tune for accuracy.Many artificial intelligence (AI) apps and services rely on deep learning to improve automation by executing analytical and physical activities without the need for human participation.

Everyday products and services (such as digital assistants, voice-enabled TV remotes, and bank fraud detection) as well as upcoming innovations use deep learning technology (such as self-driving cars).

Deep Learning for Buried Object Detection Using GPR

CNNs have recently been applied to downward-looking GPR data, inspired by their state-of-the-art performance on a number of computer vision benchmark challenges. They've shown promise in terms of identifying landmines and other explosive devices, as well as underground holes and buried objects, as well as exploring the inside of pavements and shallow geological features. When using CNNs to detect BEO from GPR data, Reichman et al. presented best practises.

The limited amount of available data necessary for training to avoid overfitting is a major challenge in most of these systems.

To overcome this constraint, some researchers have adopted approaches from the CNN literature developed in the broader computer vision field, such as data augmentation, pretraining, and transfer learning to GPR data. Bralich et al., for example, demonstrated that pretraining the network with data from several domains can increase detection performance. However, some data collections and network arrangements can lead to performance degradation.

BEO Detection Using Multiview 2-D CNNs

Detecting BEOs in GPR data acquired with an array of antennae is a 3-D classification issue in and of itself. As a result, the most natural solution is to employ a 3-D CNN architecture.

Many state-of-the-art imaging applications, including 3-D medical MRI images [55], [56], have successfully exploited 3-D CNNs for volumetric data analysis. These networks, however, are computationally more expensive than 2-D CNNs, have a larger number of parameters, and require significantly more training data. As an alternative, we consider multiview 2-D CNNs, which can benefit from both 2-D and 3-D frameworks at the same time. Individual B-scan slices are processed using a methodthat integrates partial information from orthogonal 2-D planes.

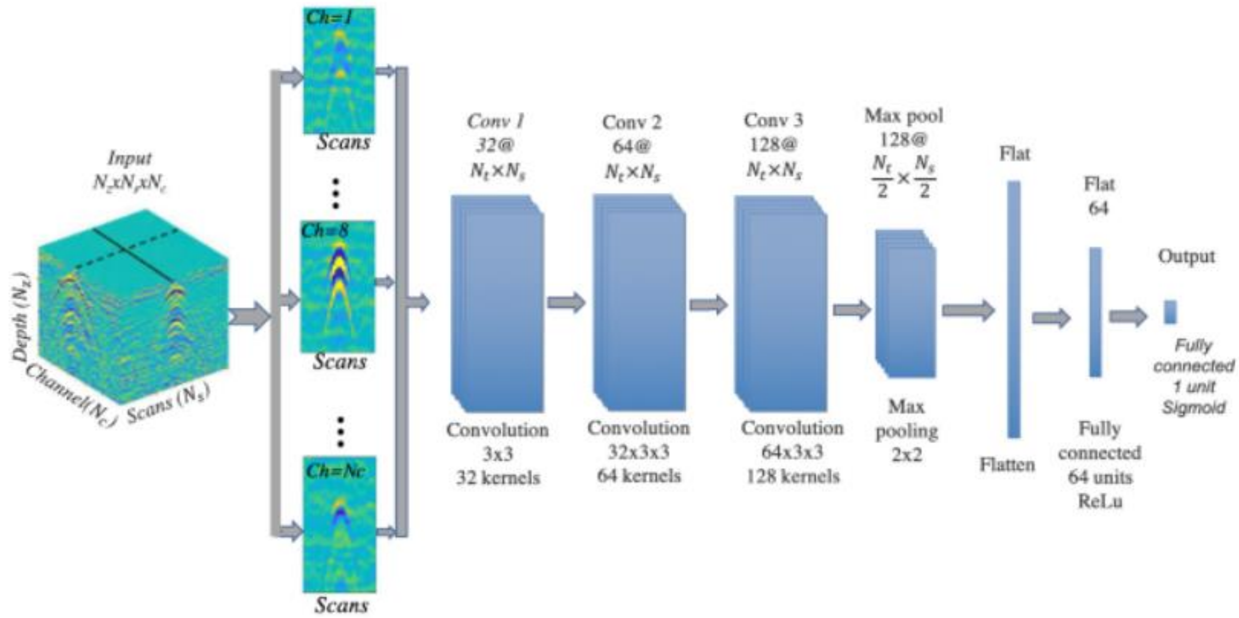


Fig. 3 The suggested CNN2 DT network architecture for processing 2-D GPR data.

The goal is to figure out when a B-scan profile in either direction could mean a BEO is present.Figure 3 depicts the architecture of the first 2-D CNN.

This network was created with the goal of extracting data from (depth, DT) B-scans. This network will be referred to as CNN2 DT, with the superscript referring to the input data dimension (2-D) and the subscript referring to the DT view. To augment the training data and learn discriminative features from adjacent B-scans, from each training alarm, we extract Nc B-scans, one from each channel, and use them as independent training samples.

The CNN2 DT architecture is made up of numerous blocks or layers that work together to analyse B-scans in a sequential manner. Convolution layers, max pooling layers, and fully connected (FC) layers are the most frequent layers utilised in most CNNs. The proposed network has two basic steps, similar to traditional CNNs: feature extraction and classification. Three convolution layers with an increasing number of kernels (N1 = 32, N2 = 64, and N3 = 128) and one max pooling layer are included in the feature extraction stage to reflect an increasing number of complicated concepts. Each convolution layer, I is made up of Ni 3 3 filters that are convolved with the B-scan picture as input.

Results

The ROCs of the CNN2 DT, CNN2 CT, and CNN2 DTCT, which combine the results of the DT and CT views using the geometric mean at each depth bin, are shown in Fig. A.

The prescreener is also shown as a reference in Fig. 4. First, both CNN2 DT and CNN2 CT outperform the prescreener, implying that 2-D CNNs may extract meaningful characteristics that can distinguish between targets and clutter objects.

Second, DT B-scans contain more discriminative information than CT B-scans, resulting in more precise discrimination.

Finally, a simple geometric fusion of the CNN2 DT and CNN2 CT networks outperforms each network individually. This demonstratesthat combining data from two orthogonal perspectives can yield additional discriminative features.

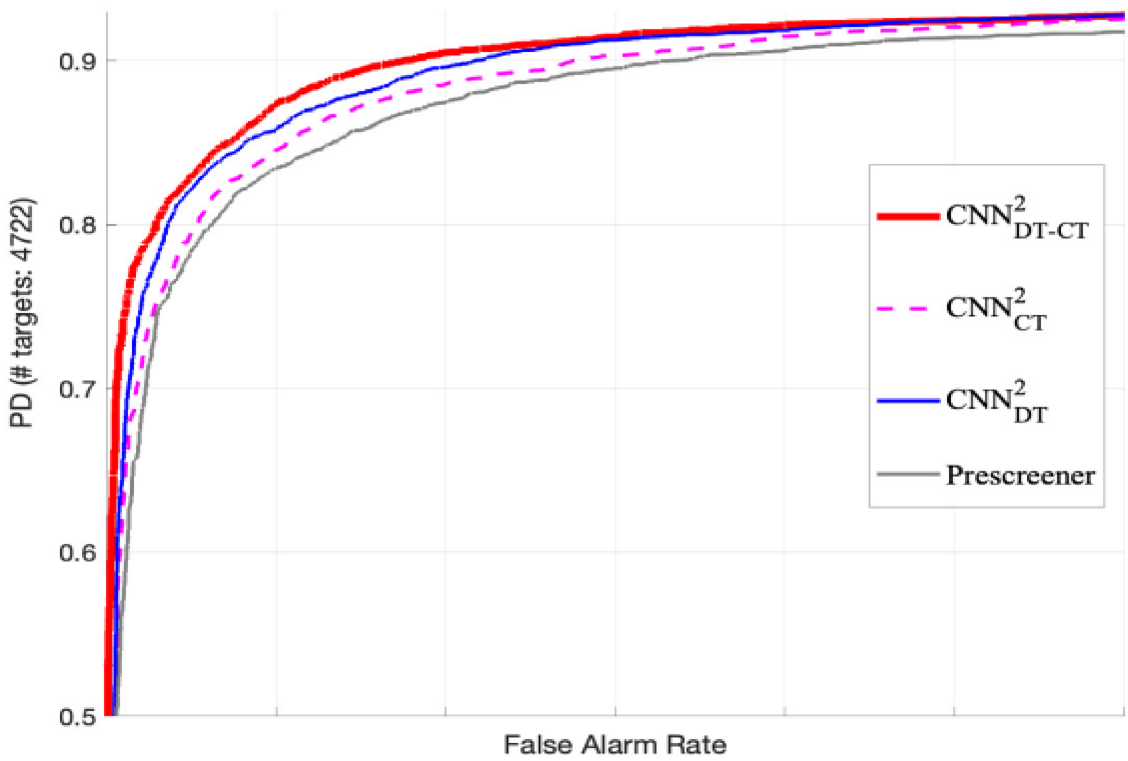


Fig. 4. ROCs obtained using the multiview 2-D CNNs

In Figure 5, the CNN–RNN ROCs are shown.CNN2 DT-RNN, which extracts features from (depth, DT) B-scans and utilises the channel index as the temporal dimension, outperforms the dual CNN2 CTRNN for these architectures.

More crucially, the depth-level fusion of the two networks improves each network significantly.

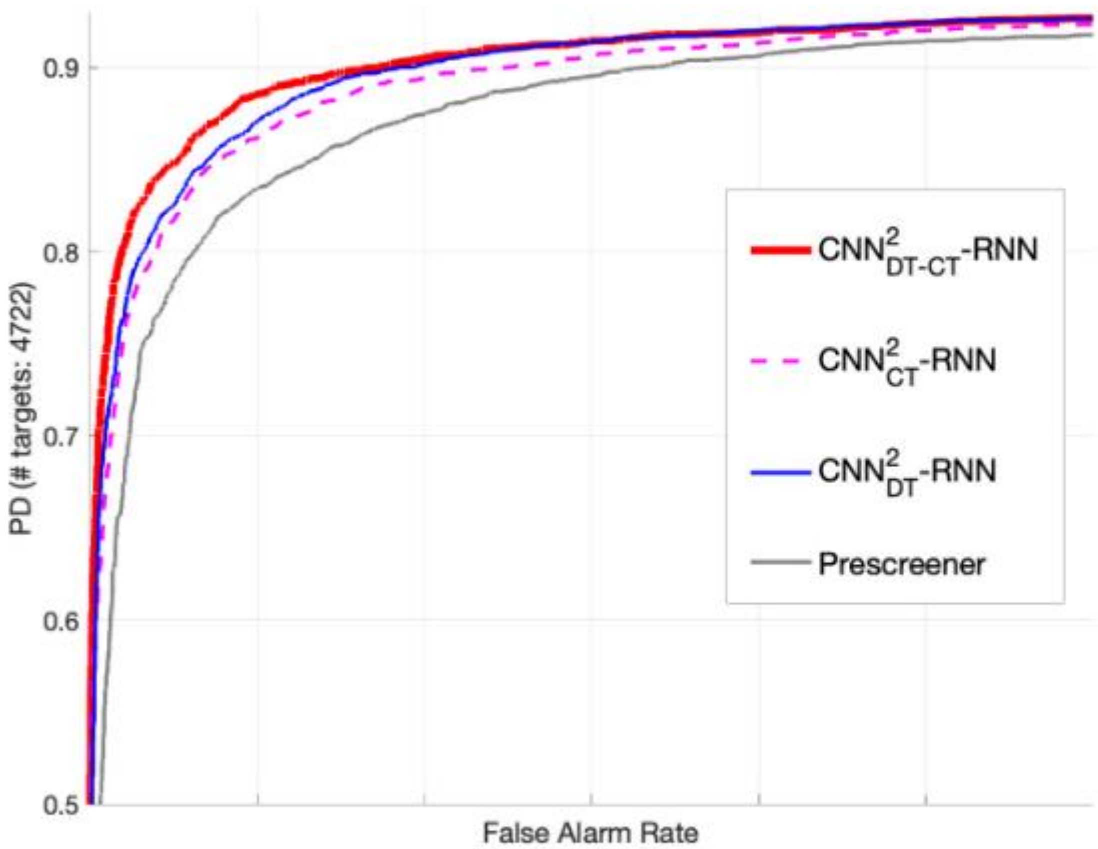


Fig. 5. ROCs obtained using a combination of CNN and RNN

Conclusion

BEO detection algorithms have largely relied on traditional machine learning that rely on hand-crafted features. Deep learning methods, on the other hand, have the ability to learn sophisticated features that optimise the entire system. These methods are the fastest growing trend in big data analysis and are increasingly being used in many application fields.

- Our proposed BTD (buried threat detection) discrimination algorithms will use deep CNNs (convolutional neural networks) and RNNs used to assess two-dimensionalground penetrating radar scans in the cartesian x and y axis directions, as well as three-dimensional ground penetrating data radar volumes.
- A chance to test new deep learning architects: For the classification issue, there are several structures or techniques available. We want to utilize MATLAB and Python because there is no foundation to start from in other languages. In the case of MATLAB and Python, we simply call the functions, adjust the input parameters, and run the tests.
- Significantly decreased programming time: Integrated libraries and commands vastly reduce design and development time. We may build, create, and test various neural network designs using minimum mathematical models and deep learning approaches.

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