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RESEARCH PAPER

A Deep Learning Method for Road Extraction in Disaster Management to Increase the Efficiency of Health Services

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Abstract

Both man-made and natural disasters can cause significant damage to property and human lives. Giving emergency medical services to the casualties as fast as possible after a disaster is critical. However, the destruction of some infrastructure such as roads, in the aftermath of a disaster, makes this process complicated. Artificial intelligence is now more frequently used to solve a wide range of difficult problems. In this paper, a combination of a deep learning model and particle swarm optimization algorithm is proposed to extract roads from satellite images, which can be useful for emergency vehicle drivers to recognize the best available path to reach casualties in disaster zones and give medical services to them faster. The model is evaluated by the evaluation metrics. Moreover, it is compared with other common models. The proposed model shows remarkable performance and 92% accuracy. Also, some predictions based on the model will be presented.

Keywords:
deep learning, metaheuristics, road extraction, disaster management, humanitarian logistics

Introduction & Literature Review

There are two types of disasters, namely, man-made and natural, both of which can cause lots of damage to property and human lives [1]. For instance, On May 12, 2008, the Great Sichuan Earthquake, which recorded a magnitude of 8.0, struck Sichuan Province, China, causing tremendous suffering for its residents. There were 88,670 deaths or missing, 374,000 injuries, and a total of over $20 billion in property damage due to the earthquake [2]. Damage or obstruction to roadways is an undeniable consequence of disasters, which hinders emergency vehicles' ability to rescue individuals [3]. Survivors of disaster impacts may suffer life-threatening injuries that require immediate medical treatment. An emergency vehicle driver should always take the fastest route possible in order to maximize the chances of saving a life. Therefore, artificial intelligence can be used to recognize the available roads based on satellite images at the moment, leading to more efficient and faster medical services for casualties.

The relationship between artificial intelligence (AI) and Industry 4.0 is symbiotic, driving a transformative wave across various sectors[4]. Industry 4.0, characterized by the integration of digital technologies into industry and process, is significantly enhanced by the capabilities of AI. AI plays a pivotal role in automating and optimizing industrial processes, leading to

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increased efficiency, productivity, and cost-effectiveness. Machine learning algorithms enable predictive maintenance, reducing downtime and enhancing overall equipment effectiveness [5]. In the context of Industry 4.0, AI serves as a catalyst for innovation, fostering the development of autonomous systems, collaborative robots, and adaptive manufacturing [6]. As industries embrace the fourth industrial revolution, the synergy between AI and Industry 4.0 promises to redefine how businesses operate, creating more agile, intelligent, and connected ecosystems [6].

A wide range of applications can be found for AI [7-9]. One of the important methods that can be used for road extraction purposes is the deep learning method, which is a subfield of artificial intelligence. Chen et al. [10] presented DeepLab, a deep convolutional neural network architecture for semantic image segmentation. DeepLab employs atrous convolution and fully connected Conditional Random Fields (CRFs) to achieve state-of-the-art results in road extraction and other semantic segmentation tasks. Xu et al. [11] proposed a DenseNet network for road extraction from remote sensing imagery.

In some research, more sophisticated networks were utilized for road extraction. Zhang et al. [12] proposed a deep residual U-Net architecture for road extraction. The network leverages residual connections to enhance feature learning and improve road segmentation accuracy. Abdollahi et al. [13] explored the use of Convolutional Neural Networks (CNNs) for road detection and extraction in high-resolution satellite images. They discussed the CNN architecture, training, and performance evaluation. Tran et al. [14] focused on road detection for autonomous vehicles and introduced a U-Net-based architecture for this purpose. The U-Net model is designed to handle real-time applications and ensure road safety.

Furthermore, some researchers used a combination of methods and technology for the mentioned purpose. Hossain and Lee [15] presented an efficient approach for road detection and tracking in aerial images using deep learning techniques. It explores the use of CNN and YOLOv3 for this task. Zhang et al. [16] explored the use of shallow multi-scale features for semantic segmentation of aerial images, with a focus on road extraction. They introduced a method to enhance road segmentation accuracy. Zhu et al. [17] investigated road extraction in very high-resolution (VHR) satellite images using CNNs. The paper outlined the CNN-based approach and evaluated its performance. Zou et al. [18] addressed road detection and tracking in urban traffic scenes with a focus on robustness. They presented a deep learning-based approach for accurate and reliable results. Wu et al. [19] proposed a MixerNet-SAGA model for road extraction and improved the precision, recall, and IoU metrics by almost 8%. Chen et al. [20] investigated building and road extraction problems and used CNN and Transformer to solve them. They tested their method on different datasets and got 76.69% and 66.41% for the IoU metric. Jing et al. [21] presented a Swin-ResUNet+ model in which a novel Swin-Transformer is used for road extraction, and they got appropriate results. A summary of the related studies is mentioned in Table 1.

Table 1. A summary of the related studies

Article	Network	Hyperparameter tuning method	Case
Chen et al. [10]	DeepLab		Various fields
Zhang et al. [12]	U-Net		Road extraction
Abdollahi et al. [13]	CNN	Common methods	Road extraction
Tran et al. [14]	U-Net	Common methods	Road extraction
Hossain and Lee [15]	CNN+YOLOv3		Road extraction
Amani et al. [9]	Deep learning	Genetic algorithm	Agriculture
Zhu et al. [17]	CNN		Road extraction
Wu et al. [19]	MixerNet-SAGA	Common methods	Road extraction
Jing et al. [21]	Swin-ResUNet+		Road extraction
Chen et al. [20]	CNN+Transformer		Road extraction
This research	Modified U-Net	PSO	Road extraction

In this paper, a combination of particle swarm optimization (PSO), a metaheuristic algorithm, and a deep learning method is utilized in the road extraction process, where PSO is used for parameter tuning in the deep learning model to increase the accuracy of the model. With the help of this method, emergency drivers can find the best available paths and reach disaster zones faster, leading to increasing the efficiency of medical services for wounded individuals in a disaster. The main contributions of this paper are proposing deep learning image segmentation methods in disaster management and reaching a model with high accuracy by integration of deep learning and metaheuristics algorithms.

The rest of the paper is organized as follows: section 2 introduces the deep learning and PSO methods, section 3 mentions the numerical results, and section 4 describes the conclusion.

Methodology

The scheme of proposed methods to build a deep learning model for road extraction is depicted in Fig 1.

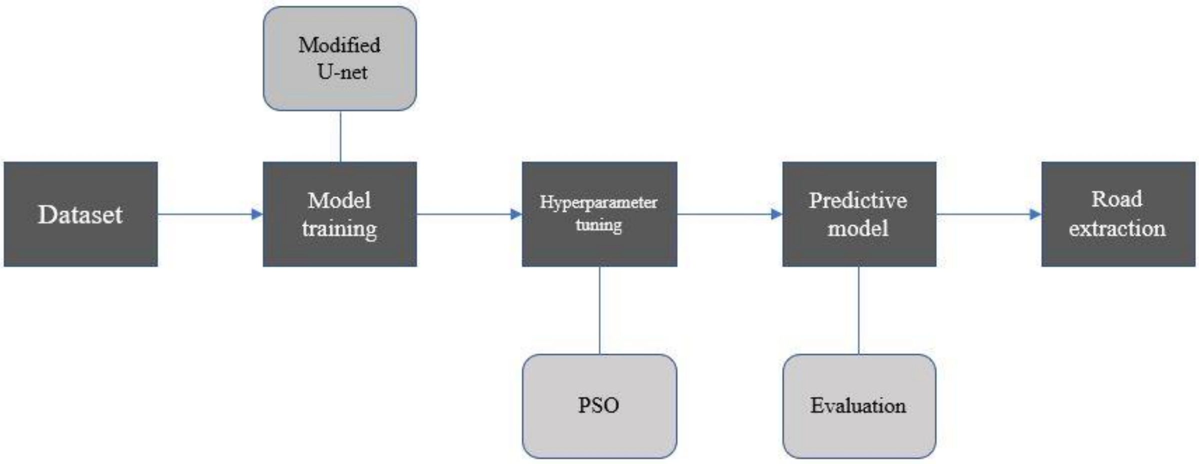

Fig 1. Scheme of the proposed methods

PSO

PSO is a metaheuristic optimization algorithm inspired by the social behavior of birds and fish [22]. PSO has gained popularity as an efficient and versatile technique for solving optimization problems [22]. The core idea behind PSO is the simulation of a social system in which individuals, represented as particles, collaborate to find the optimal solution in a search space [23]. PSO operates based on a set of key principles that drive its problem-solving capabilities [23].

In the context of solving an optimization problem, PSO initializes a population of particles randomly within the solution space [24]. Each particle's position in the space represents a potential solution, and its movement is determined by two critical components: its own experience and the experience of the best-performing particle in its neighborhood [25]. The particles then adjust their positions iteratively, seeking to move closer to the global optimum while balancing exploration and exploitation [26]. This collaborative approach allows PSO to effectively explore and exploit the search space in a decentralized manner [26]. Calculating the speed change using equation (1) determines particle movement.

$$\vec{V}_{ij}(h+1) = \varphi_1 e_1 \left(\vec{z}_{ij}(h) - \vec{x}_{ij}(h)\right) + \varphi_2 e_2 \left(\vec{z}_{gi}(h) - \vec{y}_{ij}(h)\right) + W\,\vec{V}_{ij}(h) \tag{1}$$

where $\vec{V}_{ij}(h)$ is particle i speed at h iteration, $\vec{y}_{ij}(h)$ is particle i location at h iteration, e_1 and e_2 are random numbers between (0,1), φ_1 and φ_2 are constants, $\vec{z}_{ij}(h)$ is the best location of a particle, and $\vec{z}_{gi}(h)$ is the best location of the particle swarm, and W is a constant. The new location of a particle is achieved using equation (2). The PSO algorithm flowchart is depicted in Fig 2.

$$\vec{y}_{ij}(h+1) = \vec{y}_{ij}(h) + \vec{V}_{ij}(h+1) \tag{2}$$

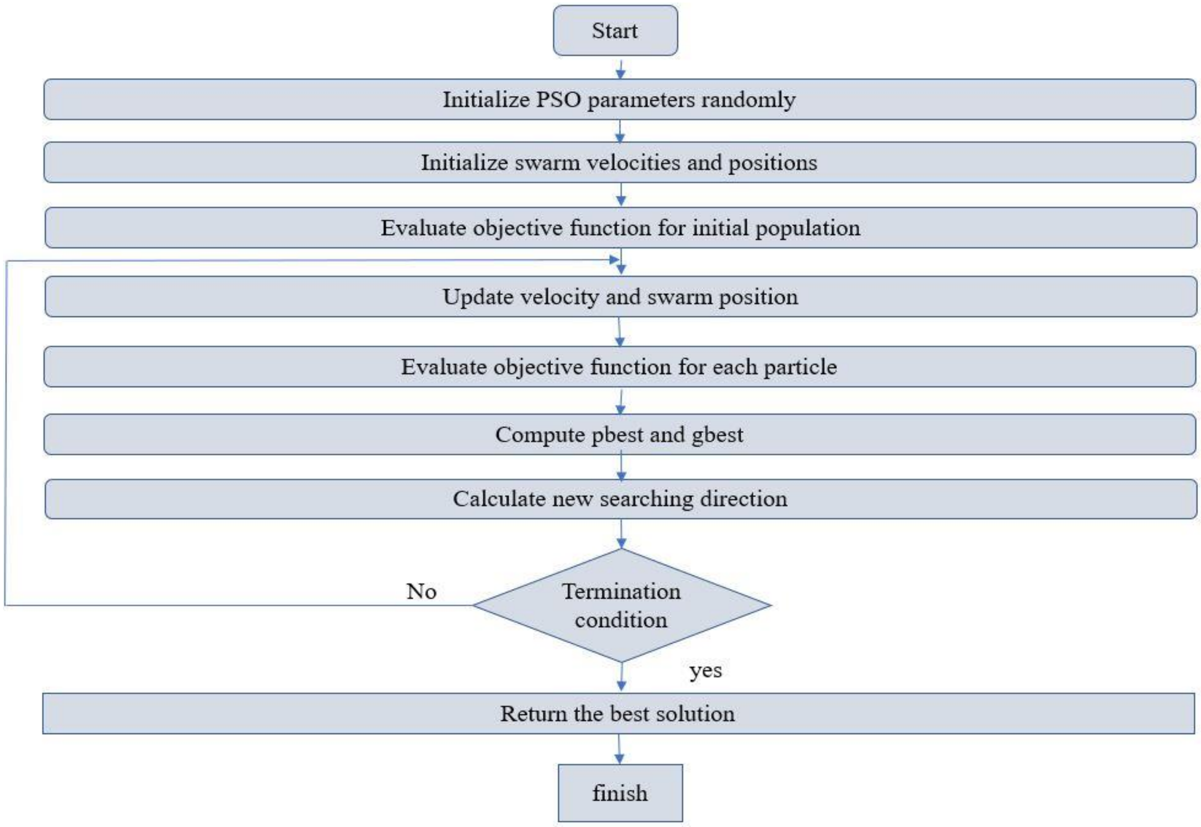

Fig 2. PSO algorithm

PSO is used in this paper to tune the hyperparameters of the deep learning model to achieve higher accuracy on the tasks.

Deep Learning

Deep learning, particularly the application of CNNs, has ushered in a new era in the field of image segmentation. Image segmentation, a fundamental task in computer vision, involves partitioning an image into distinct regions to identify and differentiate objects or structures within it [27]. CNNs have become the cornerstone technology in this domain, offering exceptional performance by automatically learning intricate features from raw image data and effectively solving complex segmentation tasks [28].

In image segmentation, CNNs are adept at both semantic and instance segmentation. Semantic segmentation assigns class labels to each pixel, thus dividing the image into regions corresponding to different object categories [29]. On the other hand, instance segmentation not only labels each pixel with the object category but also distinguishes between individual object instances of the same class [30]. CNN architectures for image segmentation include convolutional layers that capture spatial hierarchies of features, allowing them to understand the intricate relationships between different parts of an image [31]. These networks are further enhanced with techniques such as skip connections, dilated convolutions, and attention mechanisms to improve the accuracy and context-awareness of the segmentation process [31].

Image segmentation plays a crucial role in various domains, including medical imaging, autonomous vehicles, and satellite imagery analysis [32]. In medical imaging, CNN-based segmentation models are invaluable for tasks like organ delineation, tumor localization, and disease detection [33]. In the realm of autonomous vehicles, CNN-based segmentation is critical for understanding the road scene, detecting lane boundaries, identifying other vehicles, and recognizing pedestrians [34]. In satellite imagery analysis, image segmentation is used for land cover classification, environmental monitoring, and disaster response planning [35].

U-Net is a CNN architecture specifically designed for segmentation tasks in computer vision [36]. The relationship between U-Net and CNN is that U-Net is a specialized CNN variant, custom-tailored for pixel-wise classification tasks, such as image segmentation [37]. The U-net structure is depicted in Fig 3.

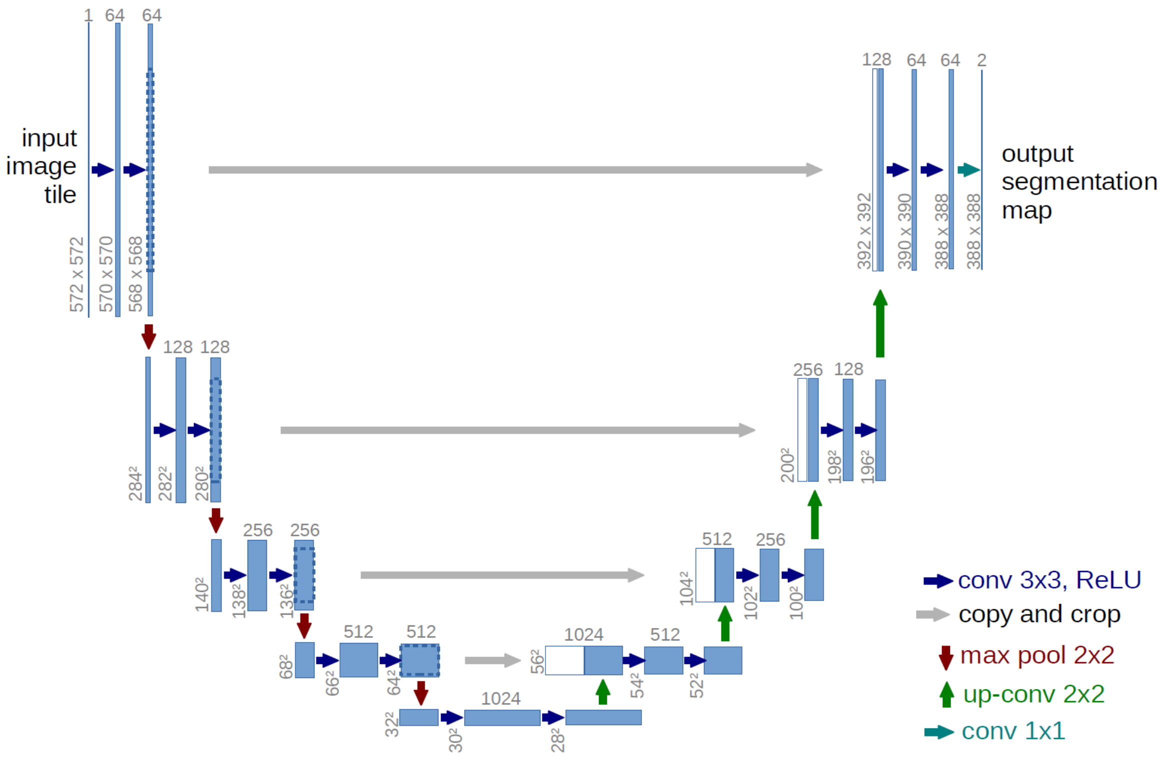

Fig 3. U-net structure[38]

Evaluation Metrics

Various metrics can be utilized for the assessment of a deep learning model, some of which are introduced as follows:

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$F1 - score = \frac{TP}{TP + \frac{1}{2}(FP + FN)} \tag{6}$$

$$Specificity = \frac{TN}{TN + FP} \tag{7}$$

If a model predicts positively and its primary amount is positive, then it is a TP, whereas a TN is when it predicts negatively and its primary amount is negative, FPs are predictions that are positive but have a negative primary value, and FNs are predictions that are negative but have a positive primary value.

Confidence Interval

The confidence interval serves as a statistical technique employed to measure and ascertain the uncertainty associated with a prediction[39]. Its application allows for the evaluation of the predictive model's proficiency and the enhancement of model robustness. The precision of the estimation hinges on the magnitude of the confidence interval, with a smaller interval leading to a more accurate estimate. Equation (8) can be used to calculate the radius of the confidence interval, providing insights into the model's accuracy and error.

$$I = Z \times \sqrt{\frac{A \times (1 - A)}{n}}$$
$$I = Z \times \sqrt{\frac{e \times (1 - e)}{n}} \tag{8}$$

where I represents the confidence interval radius, n denotes the sample size, e stands for the error, A signifies accuracy, and Z corresponds to the standard deviation value derived from the Gaussian distribution.

Numerical Results and Discussion

The dataset contains satellite images from Thailand, Indonesia, and India. It is divided into three parts: the training set (90%), the validation set (5%), and the test set (5%). Some samples of the dataset are shown in Fig 4.

Fig 4. Some samples of the dataset

Learning rate is a key parameter in deep learning models that controls how errors in estimation are addressed by updating model weights [40]. A low learning rate will prolong or even stall training processes. In contrast, too high learning rates will result in unstable training processes [40]. Convolutional layer filter numbers affect how image features are extracted from images [41]. There may be benefits in adding more filters to a CNN model, but this is not always true; therefore, the filter number should be adjusted as needed [41]. The deep learning model is trained and its hyperparameters are tuned by the PSO algorithm.

The layers used in the deep learning network, whose parameters are adjusted by PSO are noted in Table 2.

Table 2. Layers of the model

Layer
Conv2D (Relu)
Conv2D (Relu)
MaxPooing2D
Conv2D (Relu)
Conv2D (Relu)
MaxPooing2D
Conv2D (Relu)
Conv2D (Relu)
MaxPooing2D
Conv2D (Relu)
Conv2D (Relu)
MaxPooing2D
Conv2D (Relu)
Conv2D (Relu)
Conv2DTranspose
Concatenate
Conv2D (Relu)
Conv2D (Relu)
Conv2DTranspose
Concatenate
Conv2D (Relu)
Conv2D (Relu)
Conv2DTranspose
Concatenate
Conv2D (Relu)
Conv2D (Relu)
Conv2D (Sigmoid)

The evaluation of the model is illustrated in Fig 5. The result shows that the model has no overfitting problem and has proper performance. Also, the result for other metrics, which are used for model evaluation, is mentioned in Table 3.

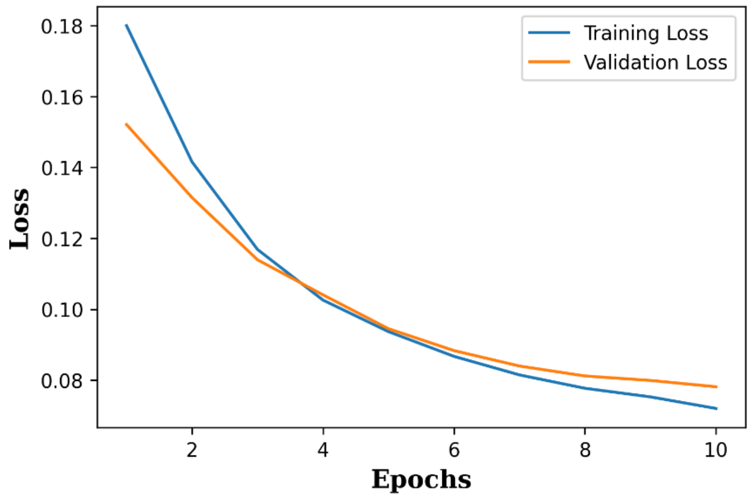

Fig 5. Evaluation of the model

Table 3. Results of the model evaluation

Metric	Value(%)
Precision	91.69%
Recall	91.69%
F1-score	91.69%
Specificity	91.69%
Accuracy	91.76%

Furthermore, the accuracy of the model is compared with some common models such as Fastai [42] and InceptionResNetv2 [43] to assess its performance better. The result is mentioned in Table 4.

Table 4. Comparison of accuracies

Model	Accuracy
Fastai	86.34%
InceptionResNetV2	85.78%
U-net	89.65%
The model (PSO + U-net)	91.76%

The determination of the confidence interval radius for the proposed model involves the utilization of Equation (8) to ensure a dependable outcome. To enhance the reliability of predictions, one can choose from four commonly used significance levels. The results obtained are presented in Table 5.

Table 5. The confidence interval radius.

Significance Level (%)	Z	Radius (%)	Accuracy Range (%)
90	1.64	± 1.4	(90.36, 93.16)
95	1.96	± 1.7	(90.06, 93.46)
98	2.33	± 2	(89.76, 93.76)
99	2.58	± 2.2	(89.56, 93.96)

Some samples that have been predicted by the model are depicted in Fig 6, which shows how the model extracts roads from the satellite images.

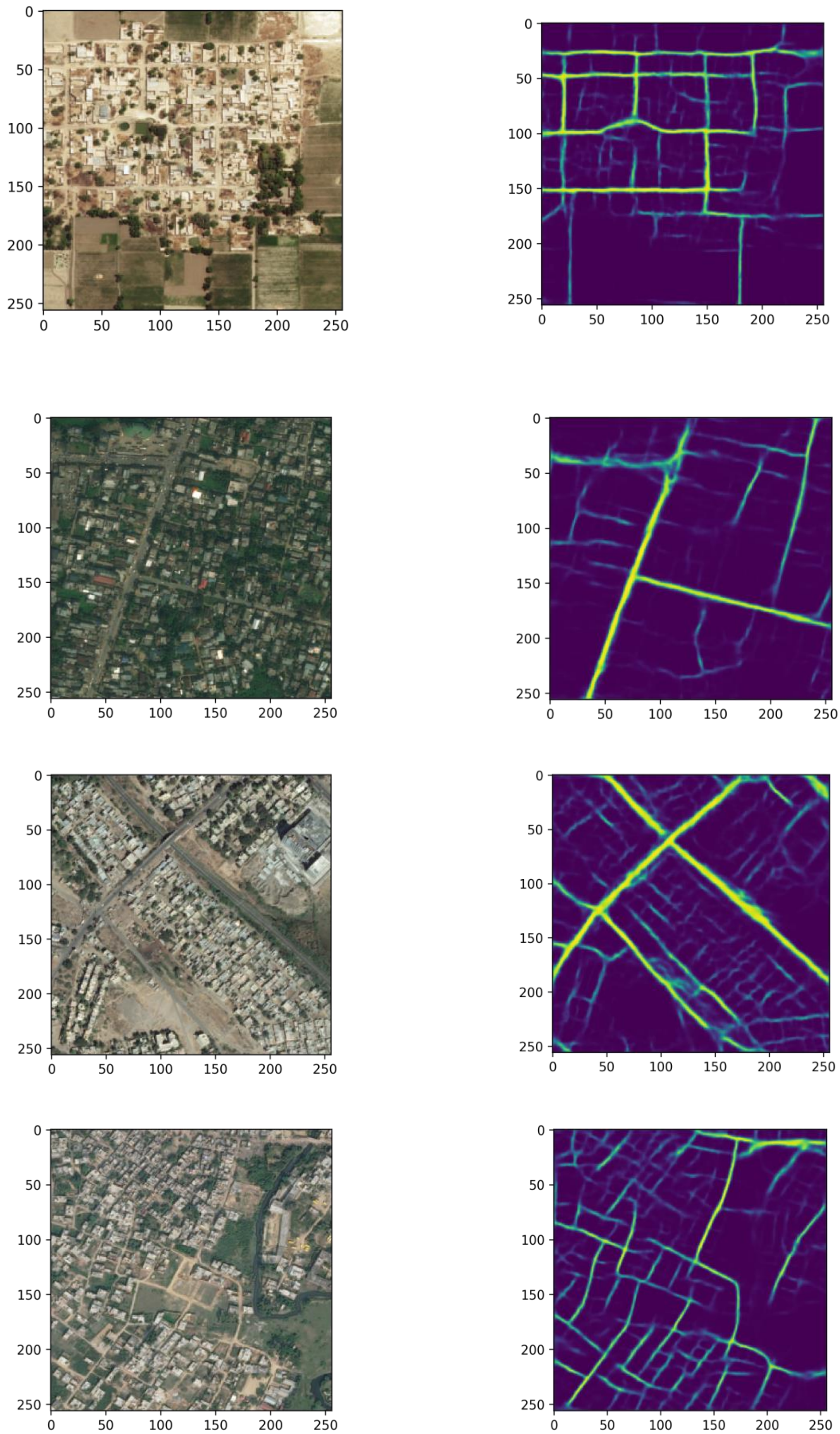

Fig 6. Predicted samples

Road extraction using deep learning from satellite images offers significant benefits in disaster management and response. One of the key advantages is the ability to quickly and accurately identify road networks in affected areas, aiding emergency responders in navigation and resource allocation. Deep learning algorithms can analyze large-scale satellite imagery datasets, rapidly detecting damaged or blocked roads, helping authorities plan effective evacuation routes and prioritize areas for immediate assistance. Moreover, this technology enhances situational awareness by providing real-time updates on the accessibility of roads, facilitating better coordination among disaster response teams. The efficiency of road extraction through deep learning ultimately contributes to faster and more targeted disaster response efforts, potentially saving lives and minimizing the impact of natural disasters on communities.

Conclusion

In this research, a combination of deep learning model and PSO algorithm is utilized to extract roads from satellite images, and the model has shown a remarkable performance, 91.76% accuracy, in comparison to other models. Also, due to that it has no overfitting problem, it is a reliable model. Furthermore, the confidence interval method is used to have a more robust model. Road extraction through deep learning from satellite images during disasters enables rapid identification of accessible routes, aiding emergency responders inefficient navigation and resource deployment. This technology enhances situational awareness by quickly detecting damaged or blocked roads, facilitating timely decision-making for disaster response teams. The swift and accurate extraction of road networks contributes to expedited relief efforts, ensuring a more effective and targeted response to mitigate the impact of disasters on affected communities. For future research, new deep learning models, novel networks, and/or metaheuristics algorithms can be utilized to increase the accuracy of the models. Also, this technology can be applied to other parts of disaster management tasks to increase efficiency.

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