ISSN: 2454-9940

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

E-Mail :
editor.ijasem@gmail.com
editor@ijasem.org

www.ijasem.org

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

Use of Deep Learning for Surveillance-Based Ground Hole Detection

[1] Mrs. A. Josh Mary, [2] Moturi Durga, [3] Malladi Jahnavi, [4]Pedapudi Keerthi Sri,

[1]Associate Professor, Dept. of CSE, Rajamahendri Institute of Engineering & Technology, Bhoopalapatnam, Near Pidimgoyyi, Rajahmundry, E.G. Dist. A.P. 533107.

[2,3,4] Students, Dept. of CSE, Rajamahendri Institute of Engineering & Technology, Bhoopalapatnam, Near Pidimgoyyi, Rajahmundry, E.G. Dist. A.P. 533107.

Abstract—

For border area security and surveillance, maintaining vigilance and detecting potential threats is of utmost importance. While surveillance drones have proven effective in enhancing border area monitoring, there are instances where ground pits can raise suspicion. Ground pits, often excavated or dug into the earth, can serve as hidden locations for various illicit activities. The inconspicuous nature of ground pits makes intruders attractive to criminals attempting to evade detection. Deep learning has shown promising potential in automating object detection through visual data. Integrating the deep learning model into drones would provide a more comprehensive and robust surveillance system. In this paper, an image dataset of ground pits referred to as Ground Pit Image Dataset (GPID) is developed to train and test YOLO. This dataset contains 300 images of different ground pits on various surfaces, captured through drones and annotated using online tools. YOLO has provided more than 90% accuracy, which is better than other deep-learning models

I. INTRODUCTION

Pits in the ground may be a security risk at borders because they can hide places where criminals can conduct their operations, penetrate border defenses, and establish links across borders. A combination of cutting-edge surveillance technology, information exchange, and joint operations across pertinent authorities is necessary to detect and react to these holes.

Authorities near the border may improve their capacity to identify and reduce ground pit hazards by using sensor systems such as ground-penetrating radar, drones, and others. In order to provide real-time situational awareness over large border regions, drones often come equipped with high-resolution cameras, infrared sensors, and sophisticated imaging systems. They outperform more conventional means of gathering aerial information, keeping tabs on operations, and spotting danger. The ability to transmit data in real-time allows border patrol officials to respond quickly to any questionable activity. Drones' ability to independently detect and identify ground holes may be further enhanced by technological breakthroughs in machine learning (ML) and artificial intelligence (AI). Using a Deep Learning technology called object detection in real-time, it is possible to extract specific items from movies and photos.

Automating ground pit identification using visual data analysis is a great way to improve safety during open excavations by recognizing possible risks and minimizing accidents. Deep learning has shown excellent results in this area.

Automated and continuous monitoring of border regions is within its capabilities. Drones make inspections and surveillance easier, freeing up security officers to concentrate on other important duties. Automatic analysis of pictures or video feeds to detect ground pits using systems based on deep learning would be a vast improvement in detection speed. One case in point is when

ISSN 2454-9940
www.ijasem.org
Vol 19, Issue 2, 2025

Fig. 1: 150-metercross-border tunnel detected by BSF along IB in Jammu and Kashmir [2]

a 150-meter tunnel hole has been constructed along the InternationalBorder (IB) to facilitate the infiltration of terroristsinto Jammu and Kashmir from Pakistan[1] as shown in Fig. 1.Hence, integrating deep learning-based ground pit detectionsystems with drones can provide a more comprehensive androbust surveillance system.With this motivation, using a drone's camera, we target topropose an automated system to identify such ground holesfor surveillance. The drone has a high-resolution camera tocapture the area of interest (border regions) as shown in Fig 2.The captured images by drone are transferred to an objectdetection system that detects the ground pits automaticallywith the help of Deep Learning techniques. Once the systemdetects any suspicious holes in the ground it marks them as apotential threat and sends this information to the appropriatesecurity agencies.Hence, this paper uses a deep learning model, especiallythe *You only look once* (YOLO) model to identify ground pitsin a smart drone's captured images in real-time. A dataset ofground pits images referred to as *Ground Pit Image Dataset*(GPID) has been developed to train and test the YOLOmodel. The GPID dataset contains approx 300 images ofground pits on various surfaces and annotated using onlinetools, e.g., Roboflow [3].We evaluated our proposed method and found the YOLO model provides more than 90% accuracy, which is betterthan other deep-learning models such as Faster-RCNN, Fast-RCNN, SSD etc. The YOLO has various variants like commontiny YOLO and YOLO v3, YOLO v5, and YOLO v8. To validatethe feasibility of GPID dataset, we use this data set to trainexisting deep-learning object detection algorithms, i.e., YOLO-version 8 with mean average precision (mAP.50) is 0.759,and mAp $(0.5 - 0.95)$ is 0.47.The rest of the paper is organized as follows: Section II surveysthe literature. Section III describes the proposed method

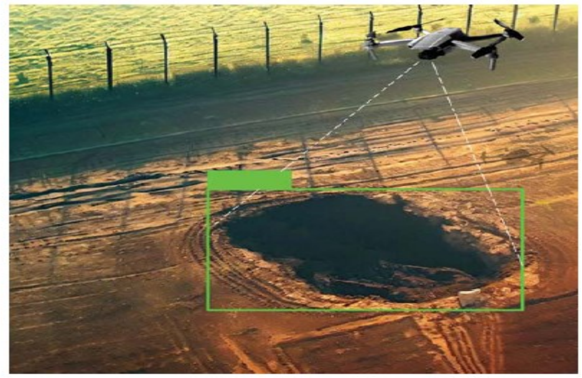


Fig. 2: Ground pit Detection through Drone

in great depth. The results of the performance analysis of the suggested procedures are presented in Section IV. The article is concluded in Section V.

II. RELATED WORKS

Autonomous driving, infrastructure maintenance, security, and surveillance are just a few of the many areas where ground pit detection has recently attracted a lot of interest. Ground hole detection has been the subject of a great deal of research [4]. In [5], the authors introduced a crowdsourcing-enabled automatic machine learning method for road pothole identification utilizing data collected from smartphone sensors. Using the smartphone's accelerometer and GPS, we were able to evaluate the surface condition of the road as well as the number of potholes.

In addition, the authors in [6] integrated ultrasonic sensors, buzzers, and a microprocessor into sticks for the visually impaired to aid with obstacle detection and smooth motion. Using an ultrasonic sensor to detect obstructions at 100 cm or less in distance was something the writers thought about while considering an Arduino IDE. The buzzer will sound an alarm to let the blind person know when it has been detected. When the depression is 18 cm or deeper, it aids in the detection of a ground hole. Eighty blind people were tested with the stick to see whether it could detect ground holes and obstructions.

In [7], the authors contemplated using drones in conjunction with deep learning and object recognition to detect and monitor forest fires. For this article, the writers scoured the web for reviews of cutting-edge drone and deep learning systems for fire detection and monitoring in forests. UAVs fitted with specialized sensors and cameras allow for efficient and cost-effective real-time surveillance and early

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT
ISSN 2454-9940
www.ijasem.org
Vol 19, Issue 2, 2025

identification of fires. Recent advances in deep learning object recognition, such as YOLO (You Only Look Once), R-CNN (Regionbased Convolutional Neural Network), and its derivatives, were thoroughly analyzed by the authors with an emphasis on their possible utility in the area of forest fire monitoring. To find the ground holes in a unique dataset, we use a deep learning method that is comparable to this one. The authors' main emphasis in [8] was on detecting potholes beside roadways. Damage to vehicles and a decline in traffic safety are two outcomes of roadside potholes. For real-time pothole identification, the author used the YOLO object detection approach. In order to identify potholes in road pictures in real-time, they used a YOLO model. A modified version of the VGG16 network is used to identify fractures in [9]. The authors trained their proposed model using their own dataset, CCD1500, and tested it using datasets from CFD, DeepCrack, and CrackTree200. Their suggested model achieves a recall of 90% on the CFD dataset, 96% on the DeepCrack dataset, and 89.10% on the CrackTree200 dataset, respectively. Based on data from accelerometers, GPS coordinates, and speed, the authors of [10] used the principal component analysis (PCA) method to classify irregularities as either long bumps, minor bumps, manholes, no abnormality, or others. This web-based program's main objective is to detect anomalies. The success rate of anomaly detection is 94% in a controlled laboratory environment, but it drops to 82% in the real world. Finding potholes in photos is as easy as following the three steps outlined in [11]. To begin, the shadowy regions around potholes are located and extracted using a histogram and the closure operation of a morphological filter. The second step is to identify possible candidates based on criteria such as the size and density of potholes. Finally, potential characteristics are used to identify the pothole. With a recall of 73.30%, precision of 80%, and accuracy of 73.50%, the suggested strategy was very effective. For image-based pothole identification, Young-Ro et al. proposed a warning system based on the Internet of Things in [20]. Once the photographs have been collected, they are transformed into binary format and then searched for occurrences of potholes in a database. According to the aforementioned research, drones used for border region surveillance still need the use of deep learning models to identify ground holes or excavations in the vicinity of borders. By finding ground pits for observation, drones may efficiently boost border area monitoring. Illicit operations may be concealed in ground pits, which are commonly sunk into the ground. Criminals looking to avoid discovery find ground holes appealing due of their inconspicuous character. So, we tackle the issue of ground pit detection in smart-drone photos using deep learning approaches. Here are the things we brought to this paper:

• In order to train our model, we create a collection of ground pit images. In order to guarantee variety in the data set, the development strategy centers on gathering photographs and picking out eligible images. Afterwards, bigger picture data sets may be generated using the same method.
In order to train and evaluate YOLO, we constructed a collection of ground pit images. There are three hundred drone-captured photos of ground holes on different surfaces in this collection.

• Using online tools such as Roboflow.com and Makesense.AI, we annotated every ground pit picture. To ensure that deep learning object identification models could handle this dataset, we tested their capabilities. The border monitoring system is anticipated to be improved with the integration of such a deep learning model into drones.

III. MATERIALS AND METHODS

This section lays out the strategy by outlining the dataset's construction and data pre-processing in great detail. Figure 2 shows the steps to get data in the YOLO format and enhance it with other data to make the dataset larger.The next sections detail the experimental design, data gathering and pre-processing procedures, and deep learning model that will be used to assess the efficacy of our suggested method. Section A: Model Details Computer vision and object recognition are only two of the many areas that have been profoundly affected by the current revolution in deep learning methods [12]. Autonomous cars, which are able to move about without a driver's intervention, are one field that stands to gain substantially from these innovations. With the goal of finding effective and reliable solutions for border area security, this research investigates the possibility of using deep learning models to identify ground holes automatically using visual data. Prior objects all make use of regions.

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT
ISSN 2454-9940
www.ijasem.org
Vol 19, Issue 2, 2025

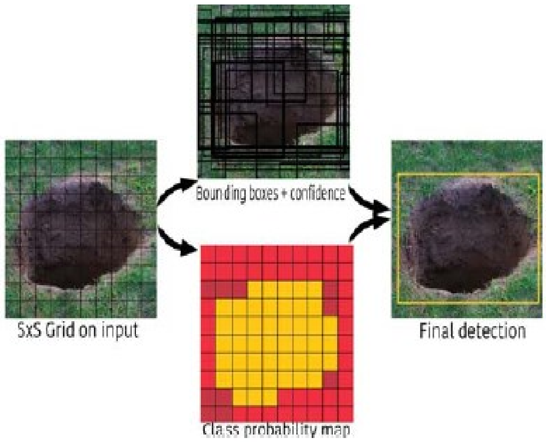
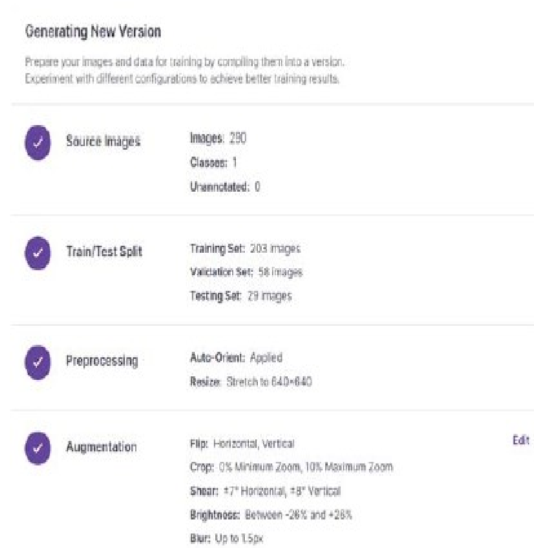


Fig. 3: Working process of YOLO

methods for detecting objects in order to localize them inside the picture. One part of the picture at a time is all the model sees. The item is more likely to be contained in certain areas of the photograph. There is a great deal of difference between region-based techniques and the object identification approach YOLO [13]. Both the bounding boxes and the class probabilities for these boxes are predicted by a single neural network model in the YOLO [14], [15]. In this study, we use the ground pit detecting capabilities of the YOLO version-8 model. Figure 3 depicts the YOLO model's process, and we'll go over its architecture here. The YOLO model divides a picture into a S × S grid. Afterwards, we determine the mth bounding box inside each S2 grid. For every one of the enclosing boxes, the model supplies a class probability along with offset values. Bounding boxes are chosen for picture selection and object localization based on whether they have a class probability greater than a predetermined threshold. The YOLO model outperforms existing object identification algorithms such as Faster R-CNN and SSD by processing 45 frames per second of the picture. The reason for this is because the YOLO model's algorithm incorporates geographical restrictions. Training The YOLO model has been enhanced with the release of YOLO-v8. Our system can identify ground holes efficiently and accurately by combining the capabilities of Deep Learning with the YOLO model. This may aid in border area safety and security monitoring. One of the essential components of the YOLO-v8 model is the Darknet, which is a Deep Neural Network architecture [16]. We adjust the network configuration to match YOLO-v8 requirements, which include the amount of layers, filters, and anchor boxes. The YOLO-v8 model modifies the architecture according to the object detection task's unique specifications.

Section B: Gathering and Preprocessing Data We constructed a set of surface photos with ground holes and called it GPID. Approximately 300 photographs of earth pits of varying forms, taken from a variety of weather and angle perspectives, make up the GPID dataset. Before the data is used to train the model, it undergoes preprocessing, which includes adjusting the picture sizes, adding annotations, and enhancing the data using various approaches. To prevent overfitting and train deep learning models to perform better, a big dataset is necessary. This is due to the fact that adding various data augmentation techniques—like scaling, cropping, resizing, flipping, rotating, and color transformations—is essential for expanding the dataset [12]. Figure 4 shows the results of this data augmentation using the web-based program Roboflow [3]. In order for the model to recognize objects, the picture dataset must be annotated with bounding boxes. We use the online annotation application MakeSense.Ai to add bounding box coordinates and class names to the photos [17]. Designed to simplify data labeling and annotation for machine learning tasks, this annotation tool is easy to use and has a focus on computer vision. Figure 5 depicts the annotating procedure.



INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT
ISSN 2454-9940
www.ijasem.org
Vol 19, Issue 2, 2025

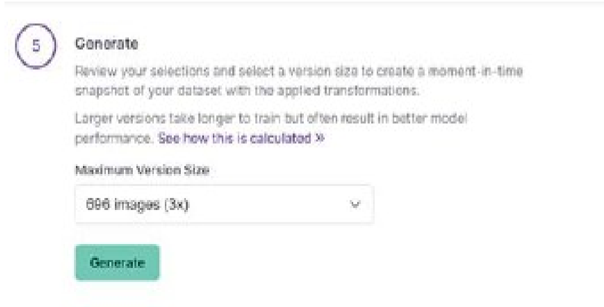


Fig. 4: Process of automatic data splitting, data preprocessing,
and data augmentation

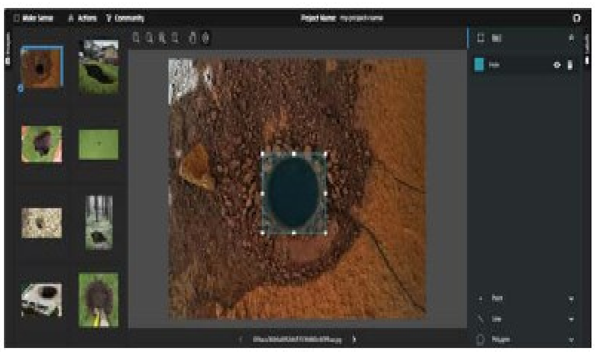


Fig. 5: MakeSense.Ai Interface

C. Experimental setup

Two separate platforms are used for this experimental configuration.

While the local computer is used for testing, the Google Colab platform is used for training the model. Phase one: Model training: The necessary tools and libraries for training YOLO-v8, such as Python, CUDA, cuDNN, and the suitable deep learning framework (e.g., Darknet, PyTorch, TensorFlow), are installed throughout the experiment. The hyper-parameters and training choices have been set up in YOLO-v8. Google Colab notebook is used for this implementation to train our model. Colab offers a powerful and user-friendly environment for executing Python code, especially for data analysis, machine learning, and research projects. It comes with a 15Gb GPU Tesla T4. Thanks to its cloud-based architecture, it can be accessed from any device with an internet connection, doing away with the need for local installation and setup. 2) Model testing: The YOLO-v8 model is tested on a computer system with a 12th-Gen Intel(R) Core(TM) i5-1240P (12 core) 4.40GHz CPU and an NVIDIA GeForce GTX 1650 graphics card with 4GB of RAM. We divided our GPID dataset in half for this experiment. In half, we trained the model using 88% of the data, tested it with 8%, and validated it with 4%.

Hyperparameters like as learning rate, batch size, and data augmentation approaches are part of the training setup. To begin training, we input the YOLO-v8 model the enhanced training data. The model generates predictions for the class probabilities and coordinates of each item in the pictures during training [18]. Observing the loss graphs in 8 allows one to track the training process. The YOLO-v8 model is trained using many hyper-parameters, including the learning rate and numerous epochs, to store the model weights at regular intervals for inference and assessment later on. After the YOLO-v8 model has been trained to our satisfaction, we will deploy it to the local computer according to the requirements specified before. Drones may use this trained model to identify objects in unseen photos or videos in real-time by integrating it into their systems. Section IV: Findings and Analysis Precision, recall, average precision (AP), and mean average precision (mAP) are some of the performance measures that have been used to assess the accuracy and detection quality of the suggested model on the separate test dataset [19]. Here are the specifics of all the measures used for evaluation: One useful tool for analyzing a classification model's output is the confusion matrix. It breaks down the data by class, showing the total number of TP, TN, FP, and FN. It is useful for evaluating the model's accuracy in class prediction and error detection. A square matrix is the usual form for its representation. Class 0 stands for the ground pit in this (Matrix.6).

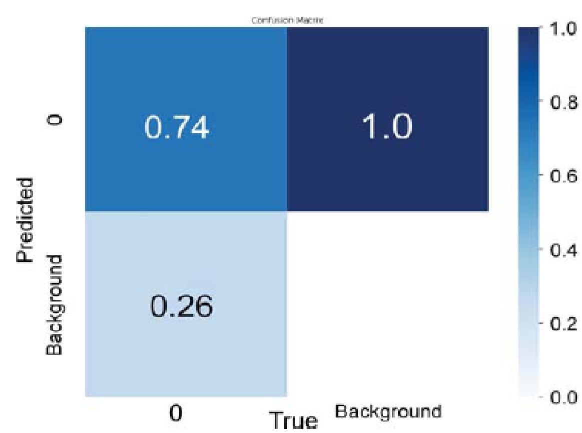


Fig. 6: Confusion matrix

2) Accuracy: This metric evaluates how well the model can distinguish between actual and anticipated positive cases. This metric specifically measures the accuracy of positive predictions and is calculated

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

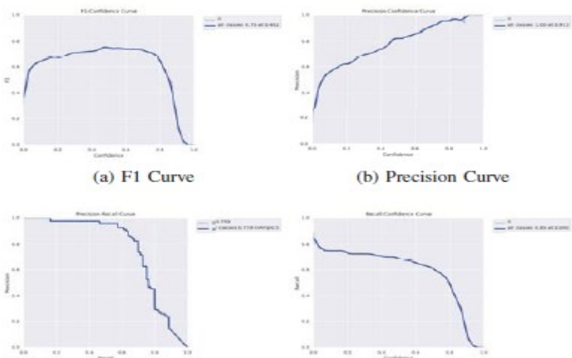
www.ijasem.org

Vol 19, Issue 2, 2025

using the following equation: it is the ratio of true positives to the total of true positives and false positives (see to Curve.7b for reference).

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

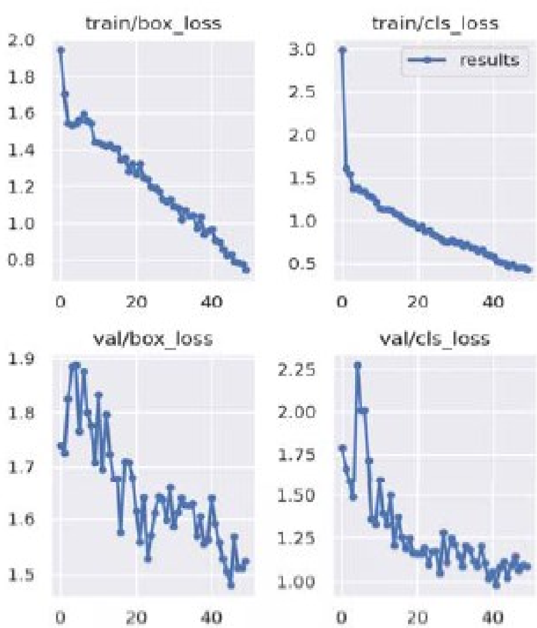
The third metric is recall, which is also known as sensitivity or the genuine positive rate. It shows how well the model can distinguish between real positive cases. See curve7d for further information; it's the proportion of correct results to the total of correct and incorrect results. It alludes to the comprehensiveness of optimistic forecasts that are computed using the equation.



(a) F1 Curve (b) Precision Curve

(c) Precision-Recall Curve (d) Recall Curve

Fig. 7: Evaluation metrics



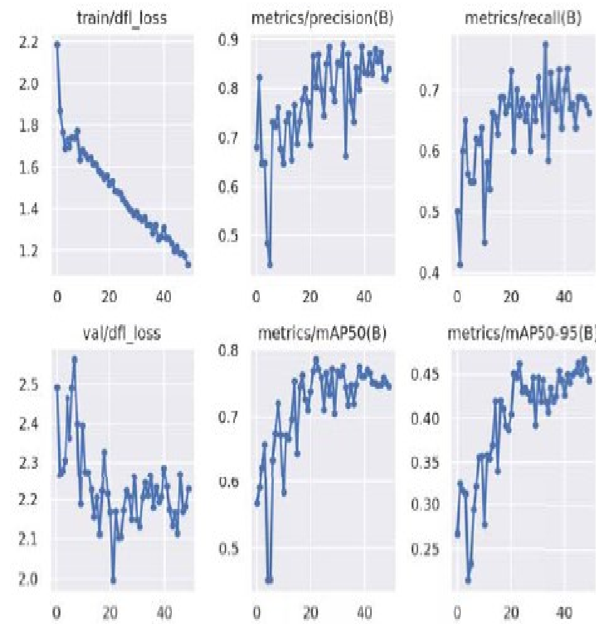


Fig. 8: Overall Results

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

4) F1 Score: A measure that consolidates accuracy and recall into one number is the F1 Score, and it may be used to assess the model's performance. The harmonic mean of recall and accuracy is represented by this statistic. To assess the model's efficacy, go to Figure 7a(a) and use the following equation.

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{3}$$

5) Mean Average Precision, abbreviated as mAP, is an assessment statistic for object identification that averages the accuracy over all recall levels. Calculating precision (7b) and recall (7d) at different confidence thresholds for object detection produces the precisionrecall (7c) curve. Area under the precision-recall curve (AP) for each class is averaged out to get the mean absolute precision (mAP). Object detection models may be evaluated using this metric. Figure 8 shows that the mean average precision (mAP.50) is 0.759 and the mAP(0.5-0.95) is 0.47.

Classification and object identification models are often evaluated using these measures, which provide insights into several parts of the model's performance, including precision, completeness, and accuracy. They are useful for finding out how well

ISSN 2454-9940
www.ijasem.org
Vol 19, Issue 2, 2025

the model predicts outcomes and for pinpointing where it may need some tweaks.

TABLE I: Comparative analysis of YOLO with other methods

Method	mAP
YOLO-v8	90.43%
Faster R-CNN	85.21%
Fast R-CNN	83.21%
R-CNN	78.02%
SSD	76.45%

Results from testing YOLO -v8 on the coverage hole/dig detection challenge are shown below. Evaluation of the model's accuracy, speed, and resilience during the analysis. As shown in Figure 8, the number of epochs is usually plotted horizontally in a standard YOLO training graphic. In these graphs, the loss value is shown along the vertical axis. One way to evaluate the model's performance during training is by looking at its loss. The model's performance is improved with lower loss levels and worsened with greater ones. During training, minimizing the loss value is the objective. After 40 epochs, losses are almost nonexistent, as seen in Fig. 8. When assessing the effectiveness of a loss in the context of YOLOv8, the terms "box loss," "cls loss," and "dfl loss" are used. The total loss figures include these. It is common practice to add all these separate losses and then apply a weight to get the total loss figure. It is implementation-dependent as to which units are used for the vertical axis. However, in most cases, they stand for the dissimilarity between the actual data and the predictions or the size of the mistake. Figure 9 displays the outcome of the working model's confidence-based predictions.

(a) prediction 1 (b) Prediction 2

Fig. 9: Result of the working model with Confidence

Table I shows the results of our comparisons with other current models, which we used to demonstrate the potential of our suggested strategy in relation to the mAP. When it comes to finding flaws in current models like R-CNN, Fast R-CNN, Fast R-CNN, and SSD, our YOLO-v8-based approach achieves an accuracy of over 90%.

V. CONCLUSION

Dug or excavated holes in the ground might provide a cover for criminal activity. Ground trenches are an enticing target for would-be invaders because of how undetectable they are. Therefore, by locating such ground pits for monitoring, drones may significantly improve border area monitoring. Finding these types of ground holes in photographs taken by smart drones using deep learning algorithms was the focus of this research. We gathered and annotated 300 photos of various sorts of earth holes on diverse surfaces to create the Ground Pit Image collection (GPID), an image collection for recognizing earth holes. A more thorough and reliable monitoring system is provided by our suggested method, which identifies ground pits with an accuracy of over 90%.

REFERENCES

[1] S. P. Kapur, “India and pakistan’s unstable peace: Why nuclear south asia is not like cold war europe,” *International Security*, vol. 30, no. 2, pp. 127–152, 2005.
[2] Wikipedia. (2023) 150-metercross-border tunnel detected by bsf along ib in jk. [Online]. Available: https://www.orissapost.com/ another-150m-cross-border-tunnel-detected-by-bsf-along-ib-in-jk/
[3] roboflow. (2023) Everything you need to build and deploy computer vision models. [Online]. Available: https://roboflow.com/
[4] Y.-M. Kim, Y.-G. Kim, S.-Y. Son, S.-Y. Lim, B.-Y. Choi, and D.- H. Choi, “Review of recent automated pothole-detection methods,” *Applied Sciences*, vol. 12, no. 11, p. 5320, 2022.
[5] C. Wu, Z. Wang, S. Hu, J. Lepine, X. Na, D. Ainalis, and M. Stettler, “An automated machine-learning approach for road pothole detection using smartphone sensor data,” *Sensors*, vol. 20, no. 19, 2020. [Online]. Available: https://www.mdpi.com/1424-8220/20/19/5564
[6] S. A. Yahaya, L. J. Jilantikiri, G. S. Oyinloye, E. J. Zaccheus, J. O. Ajiboye, and K. A. Akande, “Development of obstacle and pitdetecting ultrasonic walking stick for the blind,” *FUOYE Journal of Engineering and Technology*, vol. 4, no. 2, 2019.

[7] M. Yandouzi, M. Grari, B. Mohammed, I. Idrissi, O. Moussaoui, M. Azizi, K. Ghoumid, and K. E. Aissa, "Investigation of combining deep learning object recognition with drones for forest fire detection and monitoring," *International Journal of Advanced Computer Science and Applications*, vol. 14, pp. 377–384, 03 2023.

[8] N. Patel, V. Dabhi, and R. Adhvaryu, "Identify road potholes using image semanticsegmentation foradvance driver assistant system," *Journal of Data Acquisition and Processing*, vol. 38, no. 2, p. 2307, 2023.

[9] Z. Qu, J. Mei, L. Liu, and D.-Y. Zhou, "Crack detection of concrete pavement with cross-entropy loss function and improved vgg16 network model," *Ieee Access*, vol. 8, pp. 54 564–54 573, 2020.

[10] N. Silva, V. Shah, J. Soares, and H. Rodrigues, "Road anomalies detection system evaluation," *Sensors*, vol. 18, no. 7, p. 1984, 2018.

[11] Agrawal, K. K. ., P. . Sharma, G. . Kaur, S. . Keswani, R. . Rambabu, S. K. . Behra, K. . Tolani, and N. S. . Bhati. "Deep Learning-Enabled Image Segmentation for Precise Retinopathy Diagnosis". *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 12s, Jan. 2024, pp. 567-74, https://ijisae.org/index.php/IJISAE/article/view/4541.

[12] S.-K. Ryu, T. Kim, and Y.-R. Kim, "Image-based pothole detection system for its service and road management system," *Mathematical Problems in Engineering*, vol. 2015, pp. 1–10, 2015.

[13] N. Ahmad, S. Arya, and D. Singh, "Predicting risky environment for child inside house using deep learning," in *2023 International Conference on Emerging Smart Computing and Informatics (ESCI)*. IEEE, 2023, pp. 1–6.

[14] T. Diwan, G. Anirudh, and J. V. Tembhurne, "Object detection using yolo: Challenges, architectural successors, datasets and applications," *Multimedia Tools and Applications*, vol. 82, no. 6, pp. 9243–9275, 2023.

[15] J.-H. Kim, N. Kim, and C. S. Won, "High-speed drone detection based on yolo-v8," in *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2023, pp. 1–2.

[16] A. Melino-Carrero, A´ . N. Sua´rez, C. Losada-Gutierrez, M. Marron- Romera, I. G. Luna, and J. Baeza-Mas, "Object detection for functional assessment applications," in *International Conference on Engineering Applications of Neural Networks*. Springer, 2023, pp. 328–339.

[17] N. Ahmad, Z. Khan, and D. Singh, "Student engagement prediction in moocs using deep learning," in *2023 International Conference on Emerging Smart Computing and Informatics (ESCI)*. IEEE, 2023, pp. 1–6.

[18] Samota, H. ., Sharma, S. ., Khan, H. ., Malathy, M. ., Singh, G. ., Surjeet, S. and Rambabu, R. . (2024) "A Novel Approach to Predicting Personality Behaviour from Social Media Data Using Deep Learning", *International Journal of Intelligent Systems and Applications in Engineering*, 12(15s), pp. 539–547. Available at: https://ijisae.org/index.php/IJISAE/article/view/4788

[19] (2023) makesense.ai. [Online]. Available: https://www.makesense.ai/

[20] R. Alam, N. Ahmad, S. Shahab, and M. Anjum, "Prediction of dropout students in massive open online courses using ensemble learning: A pilot study in post-covid academic session," in *Mobile Computing and Sustainable Informatics: Proceedings of ICMCSI 2023*. Springer, 2023, pp. 549–565.

[21] N. Ahmad, A. Gupta, and D. Singh, "Using deep transfer learning to predict student engagement in online courses," in *International Conference on Machine Learning, Image Processing, Network Security and Data Sciences*. Springer, 2022, pp. 27–36.