VR SIDDHARTHA ENGINEERING COLLEGE,
VIJAYAWADA
Department of Computer Science and Engineering

Camouflages Military Soldier Detection Using Dense Deconvolutional Networks

20CS6554: B. Tech Mini Project – I (First Review)

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Batch No: 23

Batch Members

Jampani L N K Surya Sri Charan - (218W1A0586)

Bommana Phani Praharsha - (228W5A0507)

Eda Gayatri - (228W5A0508)

Thotakura Chanakya - (218W1A05C1)

Under the Guidance of

Mr. Srikakulapu Subhakar

Assistant Professor

CSE Dept

Abstract

Military camouflage is a set of techniques and patterns used by armed forces to hide personnel, equipment, and installations from observation by enemy forces. The primary objectives of military camouflage are to avoid detection, to deceive or confuse adversaries about the location or intentions of military assets, and to enhance survivability on the battlefield. This project aims to address the challenge of detecting camouflaged military personnel using deep learning techniques, through the utilization of Dense Deconvolution Networks (DDNs), an advanced variant of convolutional neural networks (CNNs). The project entails the collection of a diverse dataset comprising images containing camouflaged soldiers against various backgrounds. The DDN architecture is designed to effectively capture spatial hierarchies and feature representations within the input images, enabling the identification of camouflaged individuals with high precision through Binary segmentation. By using dense connections and deconvolutional layers, the DDN model can efficiently reconstruct spatial information lost during down-sampling operations, thus enhancing the detection outcomes.

Keywords:

Dense Deconvolution Networks (DDN), Binary Segmentation, Upsampling, Feature Extraction, Feature Map.

Presentation Outline

1. Aim

The proposal aims to develop a highly advanced model that utilizes Dense Deconvolution Networks to effectively detect camouflaged military personnel in complex visual environments. The primary objective is to enhance the accuracy and reliability of camouflaged soldier detection and Segmentation, thereby improving situational awareness and security in military operations, border control, and surveillance activities..

Motivation

By using DDNs, the project seeks to improve feature reconstruction and spatial resolution, enabling precise delineation of objects and boundaries through Upsampling of Feature map.

2. Research Questions

1. How can deep learning techniques be optimized to improve the accuracy and efficiency for detection of Camouflaged military soldier?

2. What are the most relevant and discriminative features that should be extracted from images to improve the accuracy of camouflaged soldier detection?

3. How to reduce the loss of data during Upsampling of the Feature map produced from the images which is used for detection of camouflaged soldier?

4. What can be the Advantage of packing the layers of Deconvolutional layers dense?

5. How can Binary segmentation be combined with other computer vision techniques, such as object tracking and semantic segmentation, to improve the overall performance of Camouflaged military soldier detection?

3. Title Justification

- Camouflage refers to the practice of disguising oneself or something else to blend in with the surroundings, making it difficult to be detected or recognized.

- This technique is often used in the context of military tactics, where soldiers might use camouflage clothing or paint to blend in with their environment to avoid being seen by enemies.

- DDN enables precise detection of camouflaged military personnel through the identification of subtle visual clues, disruptions in natural patterns, and contextual elements, thereby enhancing situational awareness and operational effectiveness in complex environments.

4. Objectives

1. To collect the Dataset of camouflaged military soldier Images including Ground Truth images.
2. To utilize Unet architecture model to segment the camouflaged military soldier using Dense Deconvolutional Network(DDN).
3. To generate the feature map using convolutional layers from the Image input and Upsample feature map with Deconvolutional layers.
4. To Precisely Binary segment the Soldier in image by separating the person in foreground from background.
5. To evaluate the performance of the model.

5. Scope

1. This model Detects camouflaged Soldiers in the Forests and Snow Fields of American & African Forest, American Snowfield.
2. Limited capability in segmenting very small or distant objects that might appear insignificant in the scene and struggle with multiple objects.

6. Introduction

6.1 Deconvolutional Networks

- Deconvolutional layers are used to Upsample feature maps, increasing their spatial resolution.
- These layers can be thought of as the opposite of convolutional layers; instead of reducing the spatial dimensions of the input, deconvolutional layers expand the spatial dimensions.

6.2 Upsampling

- Deconvolutional networks inherently perform upsampling of feature maps to generate high-resolution outputs. This process is essential for tasks like image super-resolution, where the goal is to generate a high-resolution image from a low-resolution input as shown in fig 1.

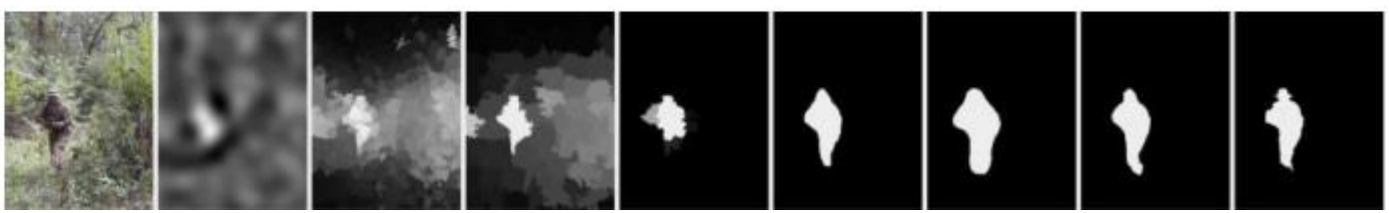


Fig 1: Comparison of camouflaged people detection maps[1]

6.3 Binary Segmentation

- Binary segmentation is a fundamental task in computer vision that involves dividing an image into two regions: foreground (object) and background.
- The camouflaged Soldiers are shown in white color and the background is shown in black color.
- Binary segmentation plays a crucial role by providing a detailed understanding of images as it classifies each pixel in the image as either belonging to the object of interest or to the background.
- Binary segmentation is a perfect method to detect Camouflaged Soldiers who blend with surroundings.

Fig 2: Segmentation of camouflaged soldier

7. Study on Existing Technologies

Title: Detection of People With Camouflage Pattern Via Dense Deconvolution Network [1]

Journal Details: Zheng, Y., Zhang, X., Wang, F., Cao, T., Sun, M., & Wang, X. (2018). Detection of people with camouflage pattern via dense deconvolution network. *IEEE Signal Processing Letters*, *26*(1), 29-33.

Dataset: own Dataset

Description:

Yunfei Zheng and team presented "**Detection of People With Camouflage Pattern Via Dense Deconvolution Network**" with a dataset of Camouflaged people Images, created from various videos with backgrounds of Wood Lands and Snow fields. The Dense deconvolution with semantic segmentation has achieved accuracy of 80% in detecting the camouflaged people.

Advantages:

1. Extraction of the semantic features in deep CNN to detect camouflaged people in images
2. Fused multiscale semantic features more effectively through Dense deconvolution network

Disadvantages:

1. Performance degradation to detect unseen classes

7. Study on Existing Technologies

Title: Efficient Camouflaged Object Detection via Progressive Refinement Network [2]

Journal Details: Zhang, D., Wang, C., & Fu, Q. (2023). Efficient Camouflaged Object Detection via Progressive Refinement Network. *IEEE Signal Processing Letters*.

Dataset: COD10K, CAMO

Description:

Zhang and team presented "**Efficient Camouflaged Object Detection via Progressive Refinement Network**" with a dataset of Camouflaged objects from COD10K, CAMO. The Progressive Refinement Network has achieved high accuracy than other models like SINet, SINetV2, JCSOD, Rank-Net, MGL, OCENet.

Advantages:

1. Better performance than other models.
2. Good balance in speed-accuracy compared with other models.

Disadvantages:

1. Can be less accurate if the person in Image is so small.
2. Performance degradation to detect unseen classes

7. Study on Existing Technologies

Title: Zero-shot camouflaged object detection [3]

Journal Details: Li, H., Feng, C. M., Xu, Y., Zhou, T., Yao, L., & Chang, X. (2023). Zero-shot camouflaged object detection. *IEEE Transactions on Image Processing*.

Dataset: CAMO, CHAMELEON, COD10K, NC4K

Description:

Haoran Li and team presented "**Zero-Shot Camouflaged Object Detection**" with a dataset of Camouflaged Object Images from CAMO, CHAMELEON, COD10K, NC4K . The inclusion of Dynamic Graph Searching Network Framework having 2 phases identification of boundary and classification of foreground and background, graph reasoning allows to pay more attention to the boundaries of objects for reducing the influences of background and detecting objects with high accuracy.

Advantages:

1. The graph reasoning helps to pay more attention to boundaries of objects reducing the influence of the background.
2. Camouflaged Visual Reasoning Generator (CVRG) is utilized to produce pseudo-features, which transfers knowledge from seen classes to unseen classes to help detect unseen objects

Disadvantages:

1. Only work for Specific background (Forest)

7. Study on Existing Technologies

Title: Camouflaged object detection via context-aware cross-level fusion [4]

Journal Details: Chen, G., Liu, S. J., Sun, Y. J., Ji, G. P., Wu, Y. F., & Zhou, T. (2022). Camouflaged object detection via context-aware cross-level fusion. *IEEE Transactions on Circuits and Systems for Video Technology*, *32*(10), 6981-6993.

Dataset: CAMO, CHAMELEON, COD10K, NC4K.

Description:

Geng Chen and team presented "**Context-aware Cross-level Fusion Network for Camouflaged Object Detection**" with a dataset of Camouflaged people Images from CAMO, CHAMELEON, COD10K, NC4K Datasets. The model is made of Context-aware Crosslevel Fusion Network (C^2F-Net) which first fuses the cross-level features extracted from the backbone using an Attention-induced Cross-level Fusion Module (ACFM) integrated with Multi-Scale Channel Attention (MSCA) allows to detect Camouflaged Objects accurately.

Advantages:

1. Dataset of diverse background
2. High accuracy in Quantitative and Qualitative Evaluation

Disadvantages:

1. Performance degradation to detect unseen classes

7. Study on Existing Technologies

Title: Towards deeper understanding of camouflaged object detection [5]

Journal Details: Y., Zhang, J., Dai, Y., Li, A., Barnes, N., & Fan, D. P. (2023). Towards deeper understanding of camouflaged object detection. *IEEE Transactions on Circuits and Systems for Video Technology*

Dataset: CAM-LDR DATASET

Description:

Zhang and team presented "**Towards deeper understanding of camouflaged object detection**" with a dataset of Camouflaged objects Images from CAM-LDR DATASET. This paper tells about the Camouflaged object detection techniques and Ranking of camouflaged objects into easy, medium and hard using R-CNN and some classification Techniques. Does comparison with state-of-art cod methods like SINet, SINetV2, JCSOD, Rank-Net, MGL, OCENet.

Advantages:

1. Ranking of dataset Images.
2. Explains About Various Techniques for Camouflaged object Detection.

Disadvantages:

1. Performance degradation to detect unseen classes

7. Study on Existing Technologies

Title: Finding Camouflaged Objects along the Camouflage Mechanisms [6]

Journal Details: Yang, Y., & Zhang, Q. (2023). Finding Camouflaged Objects along the Camouflage Mechanisms. *IEEE Transactions on Circuits and Systems for Video Technology*.

Dataset: CAMO, COD10K

Description:

Zhang and team presented "**Finding Camouflaged Objects along the Camouflage Mechanisms**" with a dataset of Camouflaged objects Images from CAMO, COD10K. This model is made of Region Distraction Module and Boundary Injection Module which detects the boundaries of the object and segments it with accuracy around 80%.

Advantages:

1. Boundaries of the Camouflaged objects are well recognized.

2. High accuracy in Feature Extraction.

Disadvantages:

1. Performance degradation to detect unseen classes

2. Only for Backgrounds of forests.

7. Study on Existing Technologies

Title: Deep texton-coherence network for camouflaged object detection [7]

Journal Details: Zhai, W., Cao, Y., Xie, H., & Zha, Z. J. (2022). Deep texton-coherence network for camouflaged object detection. *IEEE Transactions on Multimedia*.

Dataset: CAMO, COD10K, NC4K.

Description:

Zhai and team presented "**Deep texton-coherence network for camouflaged object detection**" with a dataset of Camouflaged objects Images from CAMO, COD10K, NC4K. This model is made of self designed Framework known as EAMNet which does cross refinement between edge detection and camouflaged object segmentation.

Advantages:

1. Includes various Backgrounds.
2. Outperforms other state-of-the-art COD methods.

Disadvantages:

1. Performance degradation to detect unseen classes.

7. Study on Existing Technologies

Title: Deep texture-aware features for camouflaged object detection. [8]

Journal Details: Ren, J., Hu, X., Zhu, L., Xu, X., Xu, Y., Wang, W., ... & Heng, P. A. (2021). Deep texture-aware features for camouflaged object detection. *IEEE Transactions on Circuits and Systems for Video Technology*.

Dataset: CAMO, COD10K, CHAMELEON

Description:

Ren and team presented "**Finding Camouflaged Objects along the Camouflage Mechanisms**" with a dataset of Camouflaged objects Images from CAMO, COD10K, CHAMELEON. This model is based on texture-aware refinement module (TARM) which has a 3.98% improvement on the accuracy parameters when compared to other state-of-the-art COD methods.

Advantages:

1. Higher accuracy than other models.
2. Outperforms other state-of-the-art COD methods.

Disadvantages:

1. Only for Backgrounds of forests.

7. Study on Existing Technologies

Table no.1 : Summary of existing implementations

S. No.	Article Title	Journal Details	Algorithms/ Models	Dataset	Advantages	Disadvantages
1	Detection of People With Camouflage Pattern Via Dense Deconvolution Network [1]	Zheng, Y., Zhang, X., Wang, F., Cao, T., Sun, M., & Wang, X. (2018). Detection of people with camouflage pattern via dense deconvolution network. *IEEE Signal Processing Letters*, *26*(1), 29-33.	Dense Deconvolutional Networks	Own Dataset.	1. Extraction of the semantic features 2. fused multiscale semantic features more effectively through Dense deconvolution network	1. performance degradation to detect unseen classes
2	Efficient Camouflaged Object Detection via Progressive Refinement Network [2]	Zhang, D., Wang, C., & Fu, Q. (2023). Efficient Camouflaged Object Detection via Progressive Refinement Network. *IEEE Signal Processing Letters*.	Progressive Refinement Network.	CAMO, COD10K.	1. Better performance than other models. 2. good balance in speed-accuracy compared with other models.	1. Less accuracy if the person in the image is small.
3	Zero-shot camouflaged object detection [3]	Li, H., Feng, C. M., Xu, Y., Zhou, T., Yao, L., & Chang, X. (2023). Zero-shot camouflaged object detection. *IEEE Transactions on Image Processing*.	Dynamic Graph Searching Network Framework	CAMO, CHAMELEON, COD10K, NC4K.	1. more attention to boundaries of objects reducing the influence of the background. 2. Only work for Specific background (Forest)	1. Only work for Specific background (Forest).
4	Camouflaged object detection via context-aware cross-level fusion [4]	Chen, G., Liu, S. J., Sun, Y. J., Ji, G. P., Wu, Y. F., & Zhou, T. (2022). Camouflaged object detection via context-aware cross-level fusion. *IEEE Transactions on Circuits and Systems for Video Technology*, *32*(10), 6981-6993.	Context-aware Crosslevel Fusion Network (C^2 F-Net)	CAMO, CHAMELEON, COD10K, NC4K.	1. Dataset of diverse background 2. High accuracy in Quantitative and Qualitative Evaluation	1. performance degradation to detect unseen classes

S. No.	Article Title	Journal Details	Algorithms/ Models	Dataset	Advantages	Disadvantages
5	Towards deeper understanding of camouflaged object detection. [5]	Y., Zhang, J., Dai, Y., Li, A., Barnes, N., & Fan, D. P. (2023). Towards deeper understanding of camouflaged object detection. *IEEE Transactions on Circuits and Systems for Video Technology*	R-CNN	CAM-LDR	1. Ranking of dataset Images	
6	Finding Camouflaged Objects along the Camouflage Mechanisms [6]	Yang, Y., & Zhang, Q. (2023). Finding Camouflaged Objects along the Camouflage Mechanisms. *IEEE Transactions on Circuits and Systems for Video Technology*.	Region Distraction Module and Boundary Injection Module	CAMO, COD10K.	1. High accuracy in Feature Extraction. 2. Good Boundary recognition.	1. Only for Backgrounds of forests.
7	Deep texton-coherence network for camouflaged object detection [7]	Zhai, W., Cao, Y., Xie, H., & Zha, Z. J. (2022). Deep texton-coherence network for camouflaged object detection. *IEEE Transactions on Multimedia*.	EAMNet	CAMO, COD10K, NC4K	1. Includes various Backgrounds. 2. Outperforms other state-of-the-art COD methods.	1. performance degradation to detect unseen classes
8	Deep texture-aware features for camouflaged object detection. [8]	Ren, J., Hu, X., Zhu, L., Xu, X., Xu, Y., Wang, W., ... & Heng, P. A. (2021). Deep texture-aware features for camouflaged object detection. *IEEE Transactions on Circuits and Systems for Video Technology*.	texture-aware refinement module	CAMO, COD10K, CHAMELEON	1. High accuracy	1. performance degradation to detect unseen classes

8. Gap Analysis

1. The existing Camouflaged Object Detection (COD) Systems have faced many challenges during the loss of data during feature extraction.

2. Many existing COD including State-of-art models has less explored the area of Camouflaged Military soldier and not trained any model on it.

3. Models face problem with images which have camouflaged soldiers who are far, leading to under segmentation.

4. Adaptive segmentation algorithms involved computationally intensive operations, especially when dealing with large datasets and are sensitive to noise in the input data, leading to inaccuracies in segmentation results.

9. SDLC Model

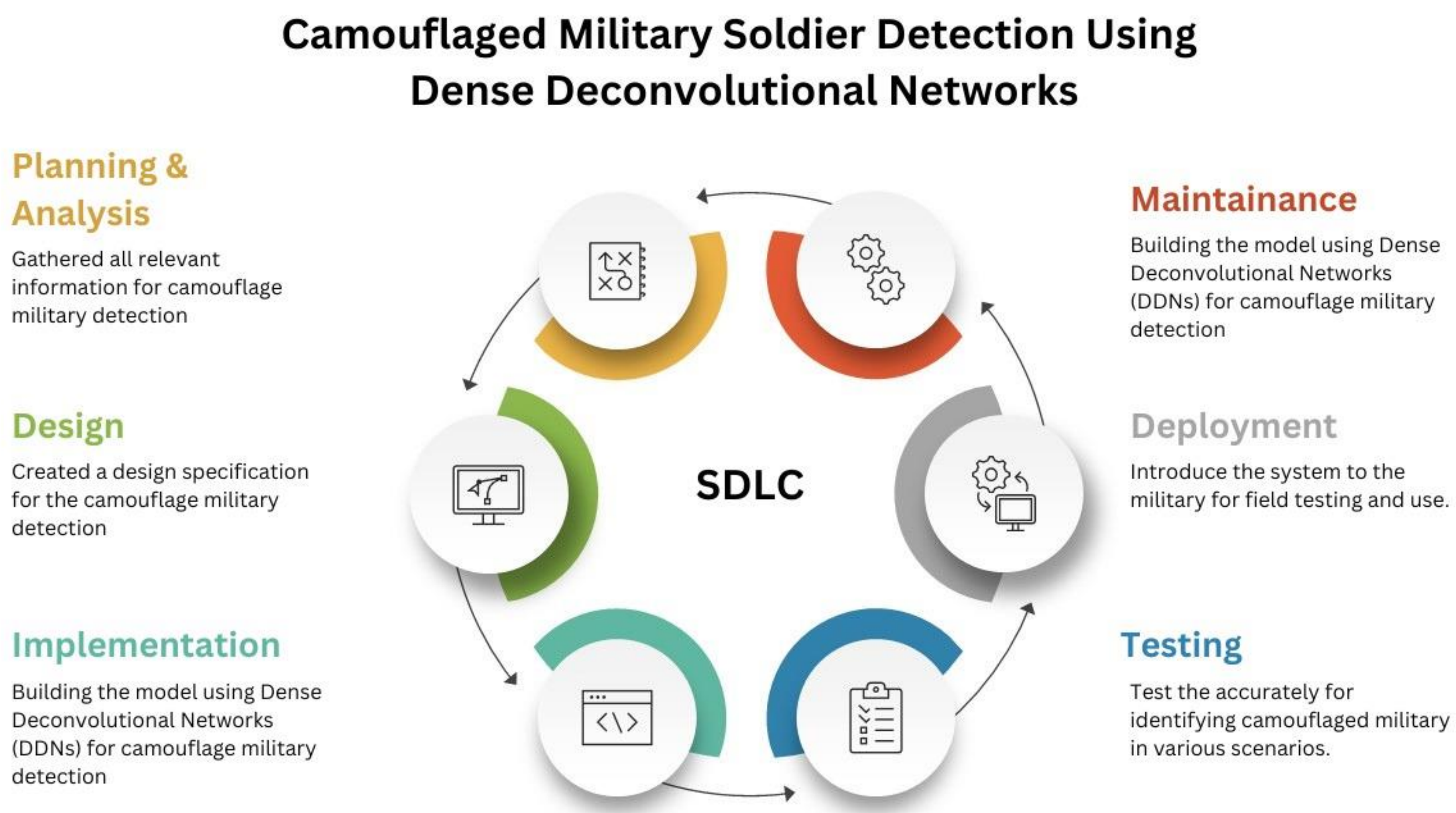


Fig 3. SDLC model of the project

10.1. Functional Requirements

Table-2: Functional requirements for Camouflaged military soldier detection

Requirement ID	Requirement	Must/Want	Comments
FR001	Data collection and analysis	Must	Gather Dataset of Camouflaged Military soldiers. Analyse historical data to identify trends and understand how feature extraction and segmentation is done through various datasets.
FR002	Feature Extraction	Must	Extraction of features from the image is the primary thing for detection of camouflaged military soldier from images. By Upsampling images by dense deconvolutional networks feature extraction is done.
FR003	Segmentation	Must	Segmentation of the person is the final output of this project.

10.2. Non-Functional Requirements

Table-3: Non- Functional requirements optimizing traffic signals through adaptive control

Requirement ID	Requirement	Must/Want	Comments
NF001	Portability	Must	Ensure that the system can be deployed across different hardware platforms and operating environments without significant modifications.
NF002	Reliability	Must	Software reliability is vital for accurate segmentation analysis, mitigating issues like bugs and hardware challenges. The system should operate reliably under normal operating conditions and handle unexpected inputs or failures gracefully.
NF003	Performance	Must	The system should process images within a specified time frame, ensuring that it meets real-time processing requirements.
NF004	Scalability	Must	Scalability is essential for the system’s seamless expansion without compromising performance. Handle varying scales of input.

11. Data Collection

Name of the Dataset: MCS1K

Description: This dataset can be used for image processing, segmentation as well as quantity estimation. It includes multiple Camouflaged Soldiers images across different American and African forests and American snowfields. Each image is annotated with pixel-level semantic segmentation labels, providing detailed information about the camouflaged soldier.

Number of Images : 2401 images

Train set size: 1496 images

Test set size: 608 images

Image resolution: 1280 x 720 pixels

12. Data Preparation

1. Data Preprocessing

Image Resizing: Since the dataset consist of multiple Images, resizing of each Image to a suitable size for model and computational resources.

Data Splitting: Divide the dataset into training and testing sets based on the provided train/test set sizes and distribution of videos from both datasets is maintained in each set.

2. Data Annotation

Each frame in the video needs to be annotated with pixel-level semantic segmentation labels and align the segmentation labels with their corresponding frames accurately.

3. Data Loading

Load the dataset efficiently during training and testing phases and using video processing libraries along with deep learning frameworks for handling video loading and manipulation.

4. Data Retrieval

The Image of specific shape is again developed from the Feature matrix values created during Upsampling (usually of shape 512,512,1)

13. Methodology

13.1. Methodology Diagram

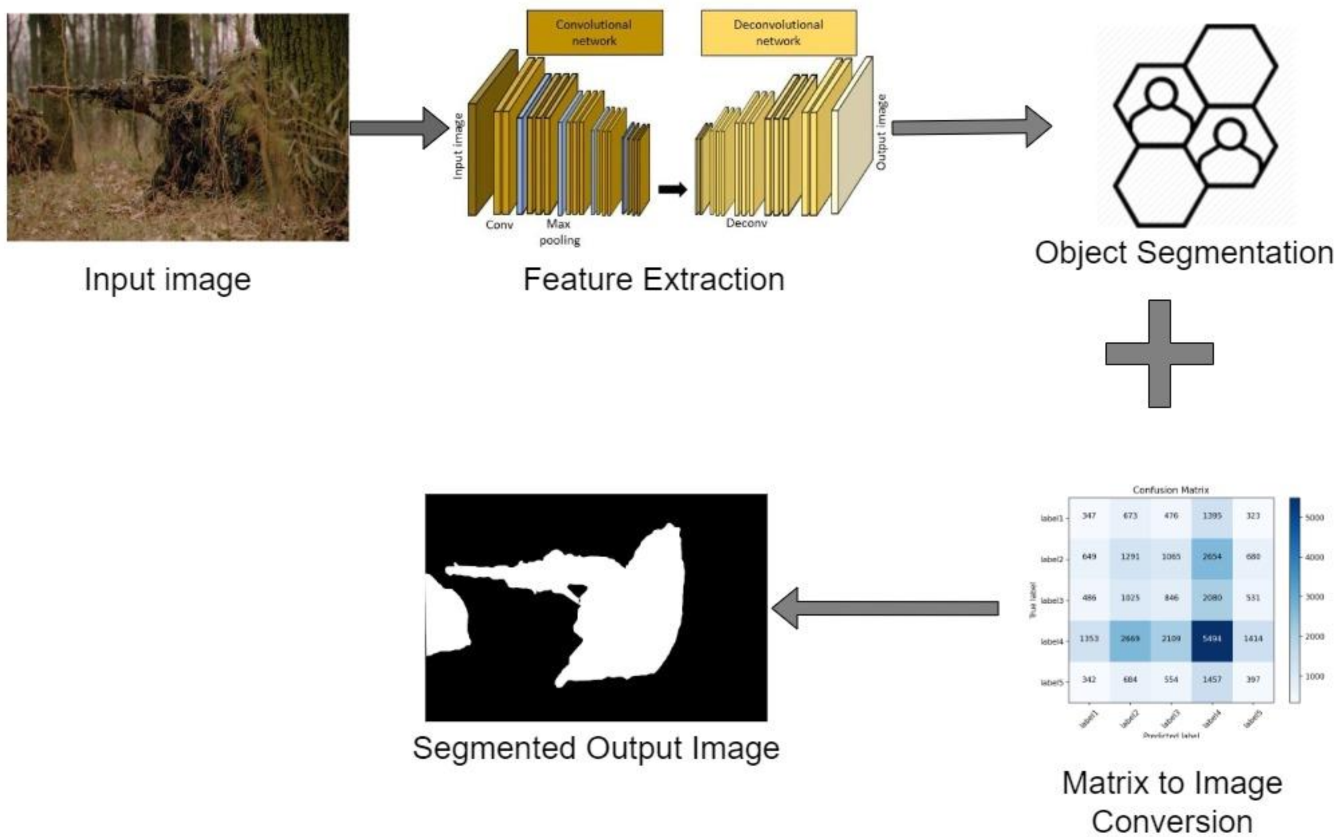


Fig 4. Methodology Diagram of the model

13. Methodology

13.1. Process flow Diagram

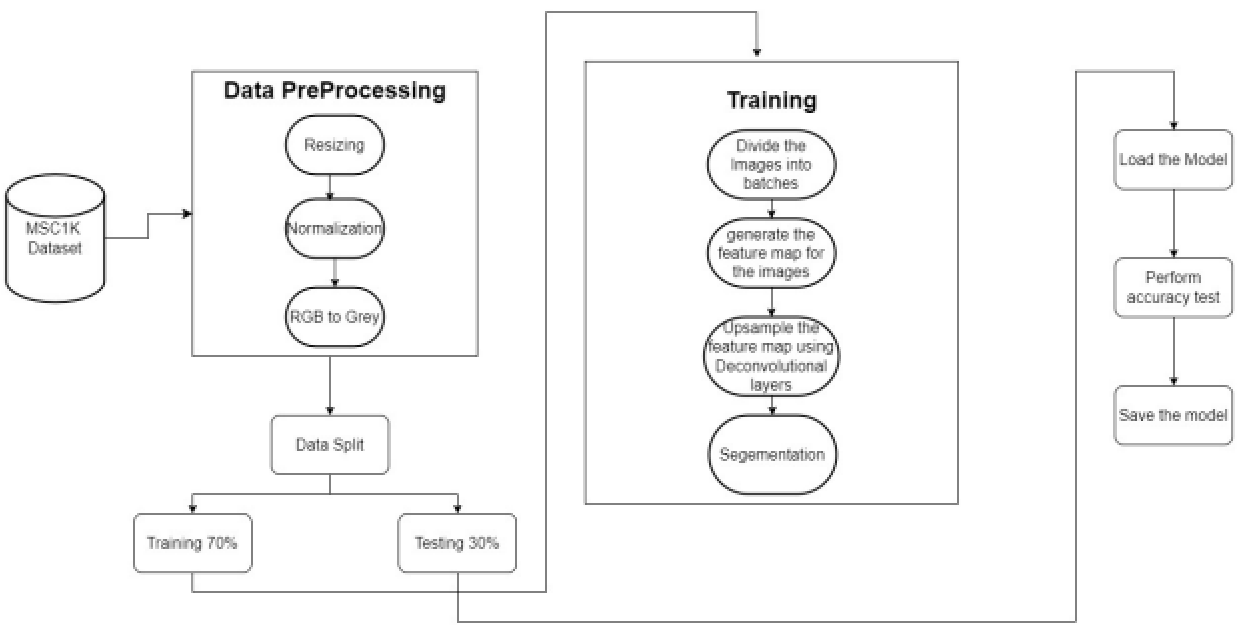


Fig 5. Process flow Diagram of the model

13.2 Architecture of Proposed Model

The Dense Deconvolutional Network(DDN) architecture of our project involves creating the feature-map of image through Downsampling using convolutional layers and extracting the features through edge detection and Upsampling by feature map using Densely set Deconvolutional layers. This approach facilitates accurate detection and segmentation of Camouflaged Military Soldier through Images.

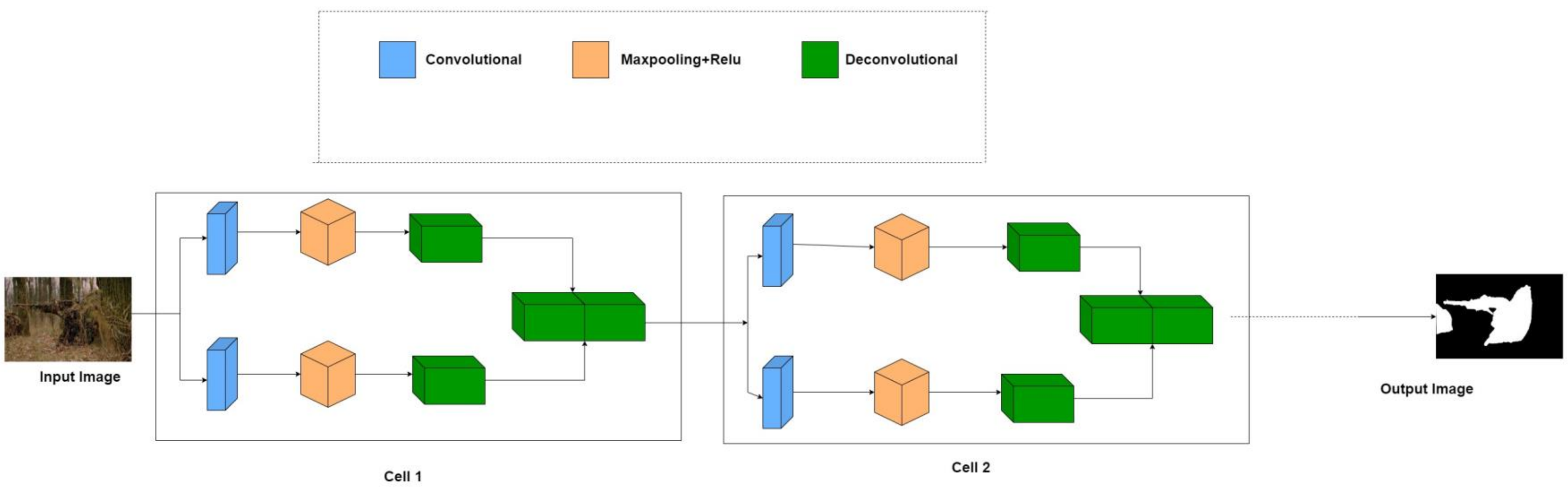


Fig 6. Architecture of Dense Deconvolutional networks

13.3. Modules of Proposed Model

Feature Extraction:

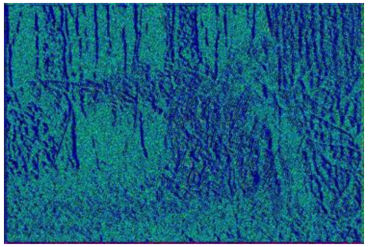
The features in the image are extracted by downsampling of the Image through convolutional layers and are stored as feature-map. Which will be in Matrix format, allowing us to perform analysis of the image.

Upsampling

The Feature-map is Upsampled through densely set Deconvolutional layers, which improves the special features in the image and reduce the loss of data.

Matrix to Image Conversion:

The Feature Matrix is Converted again into Image through Cv2 or PIL modules of a particular shape (1,472,706,3).



Segmentation:

The image extracted will undergo through the segmentation process next and Classify every pixel of the image and generates output of Segmented camouflaged Military Soldier as Image format.

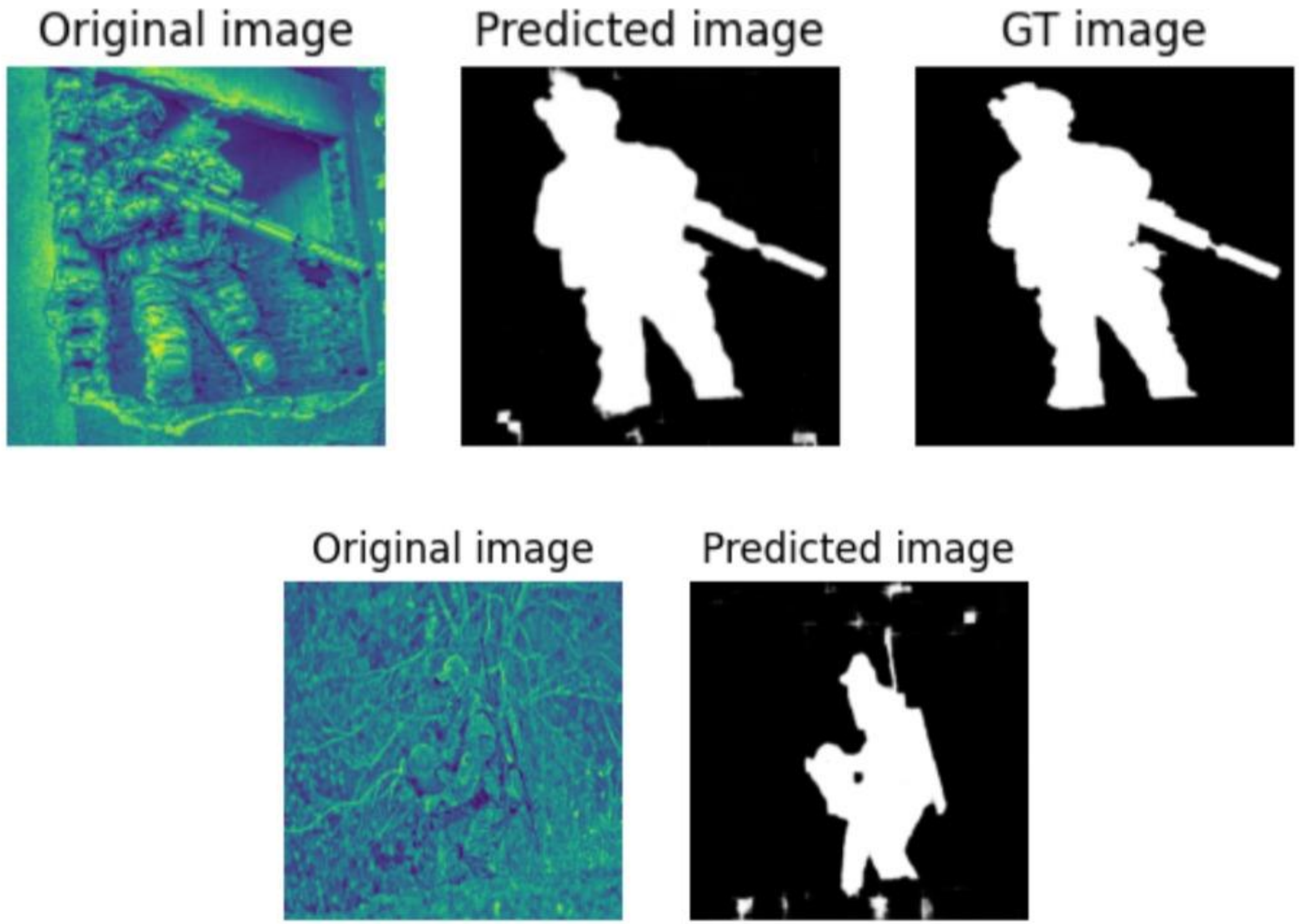
14. Timeline Chart

Table-4: Timeline chart for Mini Project – I work

Time Plan						
S. No.	**Activity plan**	**2024**				
		JAN	**FEB**	**MAR**	**APR**	**MAY**
1	Survey on existing implementations					
2	Data Collection and Preprocessing					
3	Model Implementation					
4	Evaluate performances of proposed model.					
5	Testing and Validation					
6	Comparison with other models					
7	Report Writing					
8	Paper Writing					
			Mini Project Review 0	Mini Project Review 1	Mini Project Review 2	Mini Project Final Review

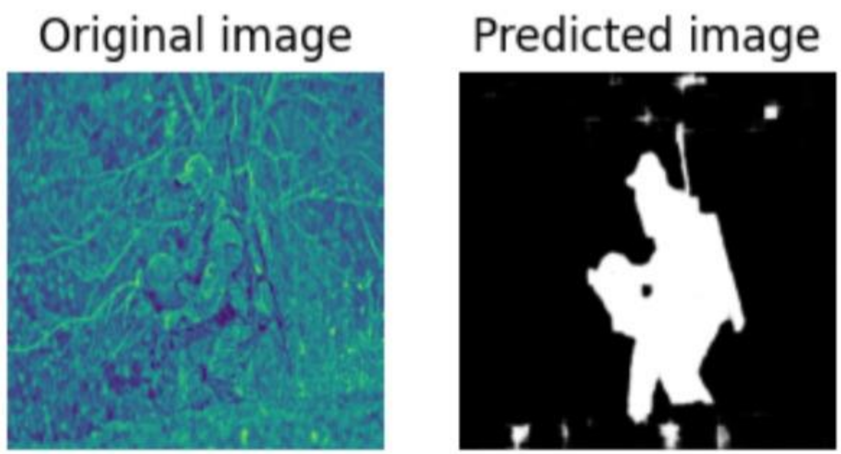
15. Result Analysis

15.1 Model Results



15. Result Analysis

15.1 Model Results



15.2 Evaluation Metrics

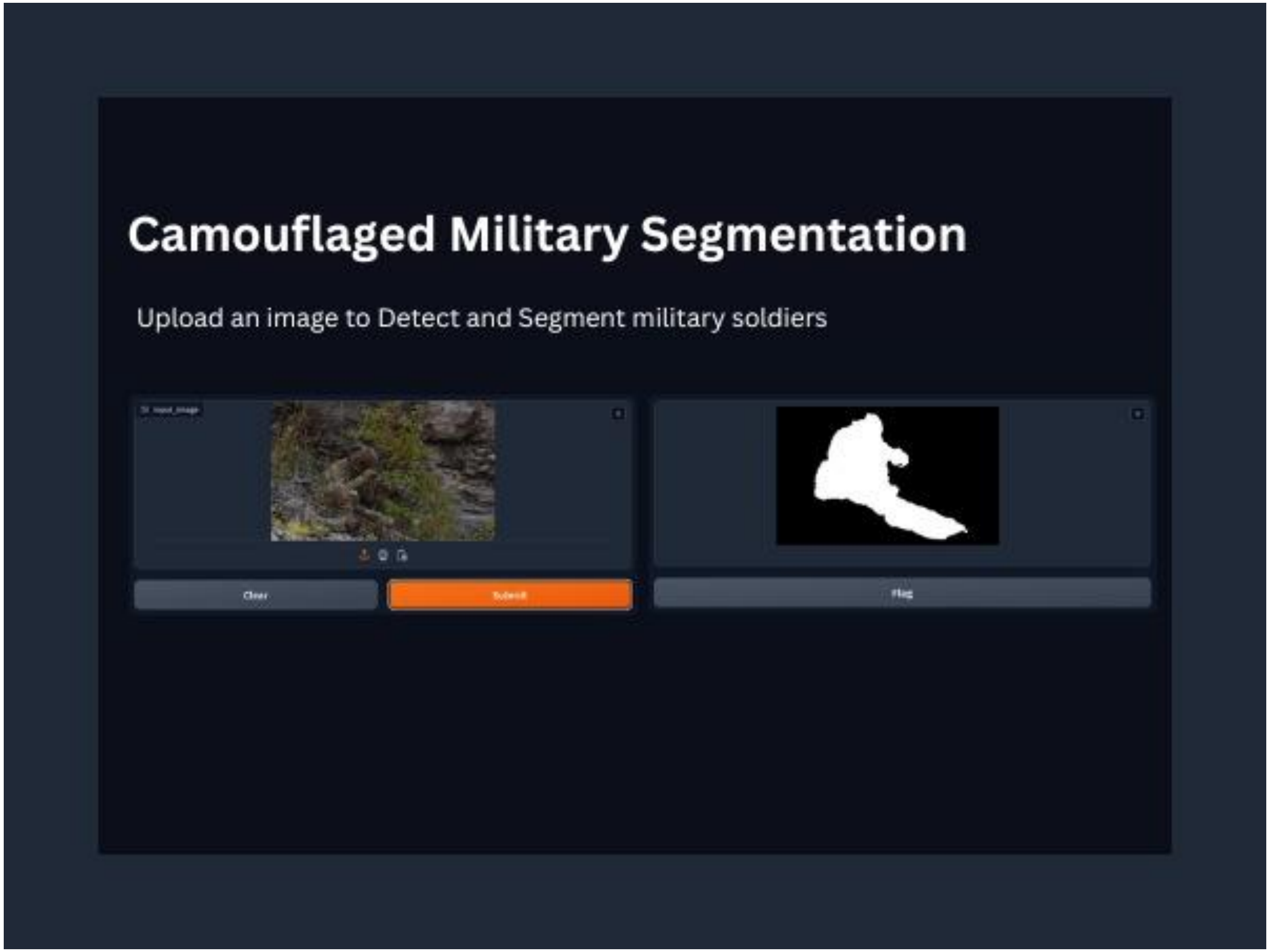
$$IoU = \frac{|P \cap GT|}{|P \cup GT|}$$

Overall IoU: 0.85165103565562

$$\text{Pixel Accuracy} = \frac{\text{Number of correctly classified pixels}}{\text{Total number of pixels}}$$

Overall Pixel Accuracy: 0.89166107177734

15.3 User Interface



15.3 Comparison Table

Literature	Model	Performance Metrics
Zheng, Y. [1]	DDN	Accuracy: 0.76
Zhang, D. [2]	PRNet	Accuracy: 0.82
Li, H. [3]	ZSCOD	Accuracy: 0.81
Chen, G. [4]	C2F-Net	Accuracy: 0.80
Y., Zhang [5]	RESNet	Accuracy: 0.79
Yang, Y. [6]	RDM	Accuracy: 0.78
Zhai, W. [7]	EAMNet	Accuracy: 0.75
Ren, J [8]	TARM	Accuracy: 0.77
Our model	DDN (unet)	Accuracy: 0.85

15. Summary

1. Implement Camouflaged Military soldier detection utilizing Dense deconvolutional networks for Feature extraction and segmentation on the dataset.
2. To Upsampled feature map for feature extraction through densely set deconvolutional layers which reduces the loss of data.
3. To developed Image again from the from the feature matrix created from Upsampling using PIL module and segmented the camouflaged soldier in it.

References

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