Armor Damage Point Segmentation Based on Improved SegNet

Zhaoyang Zuo, Xiaohe Wang, Yujiang Wang, Bo Wang, Shicheng Wei*, and Shijie Dai*

***Abstract*—Semantic segmentation of armor images faces significant challenges due to the complexity of battlefield environments and the diversity of armor types. To enhance the accuracy of armor damage point detection, we developed an improved segmentation model based on SegNet, specifically designed for segmenting armor damage. The original SegNet model suffers from limitations, including unclear segmentation and feature loss. To address these issues, we integrated the DenseNet (Densely Connected Convolutional Networks) architecture, which enables direct connections between feature maps across layers, thereby improving feature reuse and segmentation accuracy. Our model demonstrates enhanced flexibility in feature utilization compared to traditional architectures, such as U-Net and Fully Convolutional Networks (FCN), facilitating more effective feature integration. Experimental results on a specially constructed armor dataset show that our model achieves Precision of 85.32%, Recall of 83.87%, Specificity of 84.36%, and Dice similarity coefficient (Dice) of 85.9%. Additionally, our model demonstrates a 3.53% improvement in recognition accuracy while maintaining similar processing times for batches of 100 images. These results highlight the effectiveness of our model in accurately segmenting damage points under complex battlefield conditions, enabling military personnel to quickly assess armor integrity and make informed tactical decisions.**

***Index Terms*—battlefield environments, armor damage point, SegNet model, DenseNet architecture, segmentation accuracy**

I. Introduction

THE rapid evolution of modern warfare, driven by advancements in anti-armor technologies, has intensified the demand for increasingly sophisticated armor systems. Armored vehicles, such as tanks and personnel carriers, must now withstand the impact of advanced long-rod armor-piercing projectiles, shaped charges, and other high-velocity threats. Accurately detecting, assessing, and predicting armor damage is therefore critical for maintaining vehicle survivability on the battlefield [1]. However, traditional methods of manual armor damage detection and classification are time-consuming and labor-intensive, especially under the chaotic and dynamic conditions of combat [2]. Consequently, the need for automated systems capable of accurately and efficiently identifying armor damage points has become a key research priority in both military and engineering fields. These systems offer significant advantages, including higher efficiency and precision, which are essential for real-time battlefield applications.

Deep learning and neural network-based methods have emerged as powerful tools for segmenting and recognizing complex patterns, including damage points on armor surfaces. Among these methods, Convolutional Neural Networks (CNNs) have demonstrated remarkable success in various image recognition and segmentation tasks, ranging from medical imaging to autonomous driving systems [3-5]. In the context of armor damage detection, CNNs leverage their ability to analyze pixel-level information and extract relevant features from complex and noisy environments. The development of armor damage point segmentation algorithms, particularly those based on deep learning architectures such as SegNet, represents a significant advancement in automating the detection and analysis of battlefield damage to armored vehicles [6]. SegNet, a deep learning architecture originally designed for semantic segmentation, has shown considerable promise in applications requiring pixel-level classification of images. Its encoder-decoder structure is particularly well-suited for tasks such as road scene segmentation and holds potential for armor damage point detection, where precise localization of small and irregular damage points is crucial [7-8]. However, despite its effectiveness in certain segmentation tasks, SegNet's ability to handle the complexity and variability of damage points in real-world battlefield conditions remains limited. The traditional SegNet model suffers from feature loss during the encoding and decoding process, particularly in deep networks, where small-scale features may be lost or diluted, leading to inaccurate segmentation [9]. This limitation is especially critical when dealing with complex armor damage patterns caused by high-velocity penetrators, where small details are often crucial in determining the extent of damage.

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To address these limitations, researchers have proposed various modifications to the SegNet architecture, incorporating elements from other successful deep learning models such as DenseNet and ResNet. DenseNet, for instance, is a CNN architecture that enhances feature propagation by directly connecting each layer to every other layer in a feed-forward manner. This dense connectivity ensures that features learned by earlier layers are reused by later layers, thereby reducing feature loss and improving the overall accuracy of segmentation. Recent studies have demonstrated that combining DenseNet with SegNet leads to significant improvements in the segmentation of small objects and fine details, making it a promising approach for armor damage detection tasks that require high precision [10]. In addition to the integration of DenseNet, attention mechanisms have been incorporated into segmentation models to enhance their ability to focus on relevant features while ignoring irrelevant background noise [11]. Attention mechanisms enable the model to prioritize specific regions of the image based on their relevance to the segmentation task. This capability is particularly useful in armor damage detection, where irrelevant surface textures or occlusions may distract the model from accurately identifying actual damage points. The incorporation of attention mechanisms into CNNs has been shown to significantly improve segmentation accuracy, especially in noisy or visually cluttered environments [12-13]. Another important advancement in deep learning-based segmentation is the use of multi-scale feature extraction. Armor damage points can vary significantly in size, shape, and texture, particularly when considering different types of projectiles and impact angles. Multi-scale feature extraction enables the model to analyze the image at different levels of detail, ensuring the accurate detection of both large and small damage points. This approach has been successfully applied to various segmentation tasks, including medical imaging and autonomous driving, and recent research suggests that it can also enhance the detection of armor damage points [14-15].

Recent studies have shown the effectiveness of improved SegNet architectures for various segmentation tasks in complex environments. For instance, Khatri et al. [16] applied an enhanced SegNet model to detect cracks and surface damage on concrete structures, achieving significantly higher accuracy compared to traditional methods. Similarly, Chen et al. [17] developed a modified SegNet model for identifying corrosion points on steel surfaces in harsh industrial environments, proving the model's robustness in handling noisy data. These studies emphasize the potential of improved SegNet architectures for armor damage detection, especially when addressing challenges in battlefield environments, where damage points may be obscured by dirt, debris, or other occlusions. The use of deep learning for armor damage segmentation presents challenges. One of the main challenges is the need for large, labeled datasets to effectively train the models. In armor damage detection, obtaining such datasets is especially challenging because it requires detailed annotations of real-world damage scenarios. To address this limitation, synthetic data generation techniques have been used to augment existing datasets. These techniques involve generating simulated armor damage images using computer-generated models, which are then used to train the segmentation model. Although synthetic data may not perfectly replicate real-world conditions, it provides a valuable resource for training deep learning models when large-scale labeled datasets are unavailable [18-19]. Another challenge is the computational complexity of deep learning models, especially when deployed in real-time battlefield settings. The need for rapid and accurate damage assessment during combat necessitates models that can process data quickly and efficiently. Recent advancements in model optimization techniques, such as pruning and quantization, have reduced the computational burden of deep learning models, making them more suitable for real-time applications [20]. These techniques, along with advancements in hardware acceleration, have the potential to enable real-time armor damage detection and segmentation on the battlefield.

In conclusion, integrating deep learning techniques, such as improved SegNet architectures, into armor damage detection represents a significant advancement in automating battlefield damage assessment. By utilizing dense connectivity, attention mechanisms, and multi-scale feature extraction, these models can accurately detect and segment armor damage points in complex and noisy environments. The application of these methods holds great potential for enhancing the survivability of armored vehicles by enabling faster and more accurate damage assessment during combat. As research in this field progresses, further advancements in model architecture, data augmentation, and real-time processing are expected to improve the effectiveness of deep learning-based armor damage detection systems. This work marks a step forward in addressing the increasing challenges faced by armored vehicles in modern warfare and contributes to the ongoing development of more resilient and adaptive defense technologies.

II. Materials and Methods

A. Building data sets

The dataset utilized in this study consists of 27 single-layer armor images, 23 multi-layer armor images, and 47 composite armor images, all captured at a resolution of 2048 × 1536 pixels. We collected the images under diverse lighting conditions to simulate real-world battlefield scenarios and manually annotated the damage points using Photoshop to ensure high-quality ground truth data. The model was trained on a GeForce GTX 1080 GPU using the PyTorch framework. The learning rate was set to 0.001, with a batch size of 16, and the Adam optimizer was employed with cross-entropy loss as the loss function. These parameters were chosen to ensure stable and efficient training.

Data Augmentation: To improve the model's generalization ability, we applied data augmentation techniques, including random rotation, scaling, and flipping, during the training process. These techniques help the model learn invariant features and reduce overfitting. The primary objective of this study is to recognize and segment armor damage points, particularly bullet holes, which are critical for the accurate armor repair assessments. Consequently, the collected armor images were classified into two main categories: bullet holes and the surrounding background. Figure 1 illustrates the original armor image alongside its annotated damage points, showcasing the manual annotation process used to generate the ground truth data for model training.

a) Original armor image b) annotated armor damage points

Fig. 1. Results of image annotation for armor damage points

B. SegNet model

The SegNet model, a state-of-the-art deep learning architecture based on the VGG16 framework [20-21], is specifically designed for semantic segmentation tasks. The model operates in two primary stages: encoding and decoding. During the encoding phase, VGG16's convolutional layers are utilized, while the fully connected layers are omitted to enhance performance and reduce computational overhead [22-23]. This design enables SegNet to prioritize effective feature extraction, which is crucial for achieving accurate image segmentation.

The operational principle of SegNet is illustrated in Fig. 2. The encoding process involves reducing the dimensionality of the input image through a series of Max Pooling operations. Each Max Pooling operation not only down-samples the image but also records the indices of the maximum values, which is crucial for the decoding phase. The encoder consists of two 3 × 3 convolutional layers followed by a 2 × 2 pooling layer, with the ReLU activation function applied to introduce non-linearity into the model. This configuration enables SegNet to capture complex spatial hierarchies and patterns in the input data.

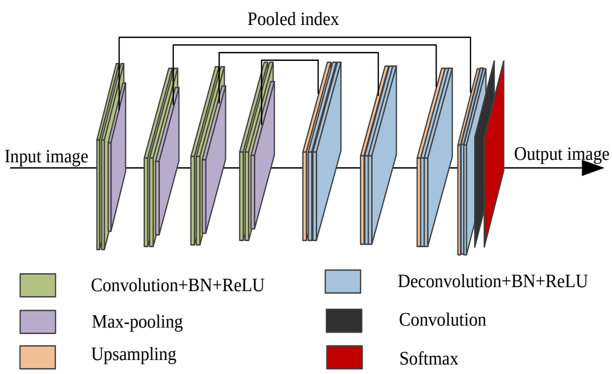


Fig. 2. Structure diagram of SegNet

The decoder phase is symmetrically designed to match the encoder. During downsampling, it is essential to preserve the positions corresponding to the maximum values obtained from the Max Pooling operations [24]. For upsampling, a scale factor of 2 is applied, and the stride is set to 2, restoring the maximum values to their corresponding positions, while setting all other values to zero. For example, if the Maximum Pooled values are denoted as a, g, j, and p, their corresponding maximum positions are retained to ensure accurate image reconstruction.

By using this upsampling method, SegNet effectively recovers the contours and positional information within the image. This capability enhances the extraction and preservation of edge features, allowing for the maintenance of the original image's size and intricate details. As a result, SegNet achieves high-precision image segmentation, making it particularly effective for identifying armor damage points [25-26]. The restored features not only improve visual accuracy but also facilitate better analysis of the segmented images, which is essential in military applications.

Finally, the output layer is connected to a multi-class Softmax classifier, which predicts the class probabilities for each pixel in the segmented image. This classification mechanism allows the model to differentiate between various classes present in the image, thereby providing comprehensive segmentation results that are vital for tasks such as damage assessment and repair strategy formulation. The transition from downsampling to upsampling is shown in Fig. 3.

Overall, SegNet's architecture balances effective feature extraction with spatial information retention, making it an ideal choice for applications requiring precise segmentation, particularly in military engineering contexts where timely and accurate damage assessment is critical. Through continuous training and validation, SegNet demonstrates considerable potential for enhancing operational effectiveness in various engineering scenarios, underscoring its significance in the field of deep learning and computer vision.

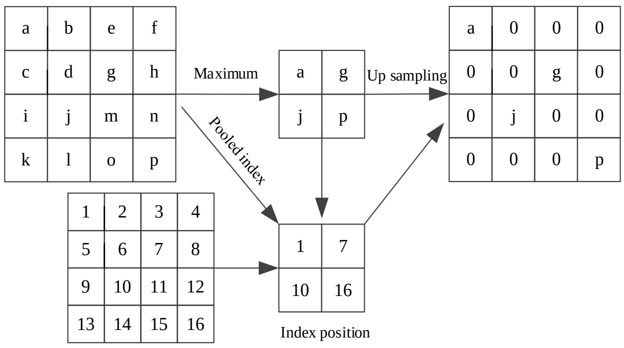


Fig. 3. The process diagram of down-sampling-up-sampling

C. DenseNet model

To enhance segmentation accuracy in CNNs, a widely adopted strategy is to increase the number of layers. However, deep networks often face challenges such as the dilution or loss of input information, while shallower networks may fail to capture sufficient detail [27]. To address these issues, Ajioka et al. [28] introduced the DenseNet architecture, which revolutionizes feature propagation within the network.

The core concept of DenseNet is its direct connectivity between feature maps across various layers, allowing for multiple instances of feature reuse. This design significantly improves the flow of information, effectively alleviating the vanishing gradient problem that often plagues deep networks. By promoting stronger propagation of image features, DenseNet enhances training efficiency and achieves higher accuracy in segmentation tasks. In this architecture, the output of each convolutional layer is concatenated with the input to the following layer. This ensures that each layer has direct access to features from all preceding layers, facilitating a richer representation of the input data. Such connectivity allows for a more compact model by reducing the number of parameters compared to traditional deep networks, thereby enhancing computational efficiency without compromising performance.

The structural design of DenseNet is shown in Fig. 4, highlighting how inter-layer connections promote effective feature learning and retention. Overall, DenseNet represents a significant advancement in deep learning methodologies, particularly for applications requiring high segmentation accuracy, such as in military engineering and image analysis. This innovative approach not only improves model performance but also opens avenues for further research in enhancing the robustness of deep learning frameworks.

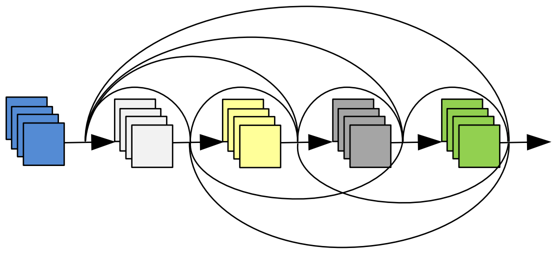


Fig. 4. Structure diagram of DenseNet

D. Improved SegNet model

When SegNet is applied directly to segment armor images, it frequently yields ambiguous and imprecise segmentation of damage points [29]. This limitation arises from the model's restricted ability to leverage multi-scale semantic information, as each decoder in SegNet processes only one scale of semantic data. Such a design leads to the loss of crucial features during the information transmission across multiple layers [30]. In response to these challenges, this paper proposes an improved version of SegNet, inspired by the DenseNet architecture.The implementation of improved SegNet maintains a structure similar to SegNet while incorporating enhancements aimed at better feature retention and utilization. As illustrated in Fig. 5, the input to this depth network is an 8-channel image, which results from merging two 4-channel images. To begin processing, Local Response Normalization (LRN) is applied to the 8-channel input in the initial layer of the depth network. This normalization step is essential for optimizing the network's performance by addressing potential issues arising from varying input magnitudes.

Following LRN, a series of convolution and pooling operations are performed to effectively extract features. Specifically, the network employs nine convolution operations and eight deconvolution operations. Each convolution and deconvolution utilizes a 3 × 3 convolution kernel, with a sliding step size of 1, allowing for fine-grained feature extraction. The pooling method implemented is maximum pooling, which uses a 2 × 2 sliding window with a stride of 2, enabling dimensionality reduction while preserving essential information.

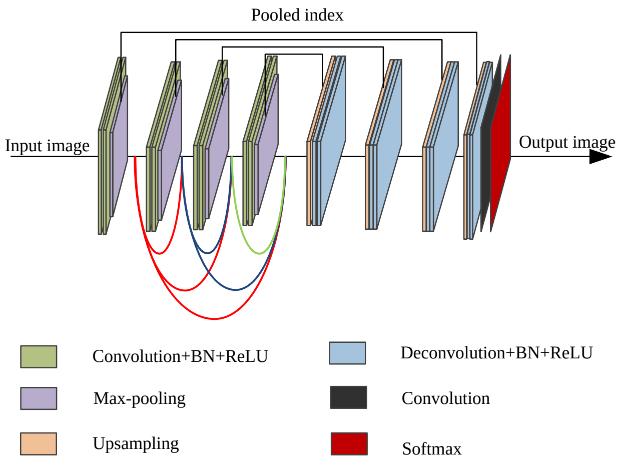


Fig. 5. Structure diagram of improved SegNet

After the convolution and pooling stages, the model performs multiple upsampling and deconvolution operations. Here, "deconvolution" refers to the transpose convolution, which serves to reconstruct the spatial dimensions of the feature maps to their original size. The final output of the network is generated through a convolution operation followed by a Softmax function, which produces a K-channel probability image. In this context, K denotes the number of output categories. For this experiment, which distinguishes between background and damage points, K is set to 2. Detailed implementation parameters of improved SegNet are presented in Table 1.

TABLE I
THE IMPLEMENTATION PROCESS OF IMPROVED SEGNET.

Operation	Output Image (Width, Height, Channels)
Input Image +LRN	(224, 224, 8)
Convolution +BN+ReLU	(224, 224, 64)
Convolution + BN+ReLU	(224, 224, 64)
Maximum Pooling	(112, 112, 64)
Convolution + BN+ReLU	(112, 112, 128)
Convolution + BN+ReLU	(112, 112, 128)
Maximum Pooling	(56, 56, 128)
Convolution + BN+ReLU	(56, 56, 256)
Convolution + BN+ReLU	(56, 56, 256)
Maximum Pooling	(28, 28, 256)
Convolution + BN+ReLU	(28, 28, 512)
Convolution + BN+ReLU	(28, 28, 512)
Maximum Pooling	(14, 14, 512)
Up Sampling	(28, 28, 512)
Deconvolution + BN+ReLU	(28, 28, 256)
Deconvolution + BN+ReLU	(28, 28, 256)
Up Sampling	(56, 56, 256)
Deconvolution + BN+ReLU	(56, 56, 128)
Deconvolution + BN+ReLU	(56, 56, 128)
Up Sampling	(112, 112, 128)
Deconvolution + BN+ReLU	(112, 112, 64)
Deconvolution + BN+ReLU	(112, 112, 64)
Up Sampling	(224, 224, 64)
Deconvolution + BN+ReLU	(224, 224, 64)
Deconvolution + BN+ReLU	(224, 224, 64)
Convolution	(224, 224, 2)
Softmaxclassifier	

In addition to Convolution operations, Batch Normalization (BN) is applied after each Convolution and Deconvolution operation, excluding the last Convolution. The inclusion of LRN and BN techniques is primarily to facilitate network training and enhance convergence speed, thus optimizing the overall training process.

Compared to other state-of-the-art architectures [31], Improved SegNet significantly reduces the number of parameters in the encoder network, making it more computationally efficient. Additionally, two widely used architectures, FCN and U-Net, share structural similarities with improved SegNet but also exhibit key differences. FCN requires a higher level of parameterization, leading to increased computational demands and making end-to-end training more challenging. This complexity largely stems from the inclusion of fully connected layers, even when implemented in a convolutional manner.

On the other hand, U-Net [20] takes a different approach. Instead of reusing Pooling indices, as improved SegNet does, U-Net transfers entire feature maps to corresponding decoders, which incurs higher memory usage. These feature maps are then concatenated with upsampled decoder feature maps via transposed Convolutions. Another notable distinction is that U-Net lacks the Conv5 and Max-Pool5 blocks present in the VGG network architecture. This difference impacts the depth and hierarchical feature extraction capability of the network.

In contrast, Improved SegNet uses all pre-trained convolutional layer weights from the VGG network as initialization weights. This design choice not only improves feature reuse and computational efficiency but also ensures robust performance by building on a well-established feature extraction backbone. These advantages position improved SegNet as a highly efficient and accurate architecture for semantic segmentation tasks.

A key aspect of the improved SegNet architecture is the incorporation of outputs from earlier layers after each Pooling operation. This integration is vital for retaining the multi-scale feature information that is typically lost in standard models. However, it is important to ensure that the outputs from the preceding layers are pooled to align with the size of the current Pooling output. For instance, after the first maximum Pooling operation, the input from the first layer requires one Pooling operation to adjust its dimensions. During the second Pooling phase, both the input from network layer 1 and the results from the first Max Pooling need to be processed, necessitating two Pooling operations on the layer 1 input and one on the result from the first Pooling. Similarly, after the third Maximum Pooling operation, introducing the outputs from the first layer and the two previous Max Pooling results requires three Pooling operations on the first layer input, two on the first Max Pooling result, and one on the second Max Pooling result.

This systematic approach to layer integration and feature management within improved SegNet model is intended to enhance the model's ability to accurately segment armor damage points, ensuring a more robust performance in applications requiring precise image analysis. The proposed architecture aims to effectively combine multi-scale semantic information, ultimately improving the clarity and accuracy of segmentation outcomes.

Finally, morphological operations are employed as a post-processing step to refine the semantic segmentation results and enhance their quality. These operations are essential for reducing image noise, filling gaps, and enhancing the key features in the segmented image. The primary goal is to retain relevant information while removing unnecessary elements, thereby improving the overall segmentation performance.

Common morphological operations include dilation, erosion, opening, and closing [32]. Dilation works by expanding or thickening objects in an image, helping to connect small gaps, while erosion shrinks or thins objects, which is useful for removing small artifacts. The opening operation involves erosion followed by dilation, efficiently removing noise and filtering out small, irrelevant objects. In contrast, closing involves dilation followed by erosion, which helps merge small disconnected components and smooths boundaries, thereby filling gaps or holes in objects.

In this study, we chose to use the closing operation as the preferred post-processing technique because of its ability to enhance the continuity and coherence of the segmented objects. Closing is especially effective for improving the quality of armor damage point segmentation, as it helps merge fragmented regions and fill small holes in the detected damage points. By using closing as a post-processing step, we ensure a more accurate and refined final segmentation result, which ultimately contributes to better damage assessment in armor images.

III. Results

A. Accuracy evaluation index

Several key accuracy metrics are employed to assess the performance of segmentation models, including Precision, Recall, Specificity, and Dice coefficient. These metrics collectively provide a comprehensive assessment of the model's effectiveness in detecting damage points in armor images.

The formulas for calculating these metrics are as follows:

$$Precision = \frac{TP}{TP + FP} \times 100\% \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \times 100\% \tag{2}$$

$$Specificity = \frac{TN}{TN + FP} \times 100\% \tag{3}$$

$$Dice = \frac{2TP}{FP + 2TP + FN} \times 100\% \tag{4}$$

Where TP denotes the number of pixels accurately identified as damage points, FP represents the number of pixels erroneously classified as damage points, TN indicates pixels correctly recognized as background, and FN refers to pixels mistakenly identified as background. Dice coefficient quantifies the overlap between the segmentation output and the ground truth, serving as a pivotal metric for evaluating the model's accuracy in generating reliable segmentations.

B. Training results

After completing the training phase, we evaluated the model's accuracy on a designated test set. The statistical analysis of model performance is summarized in Table 2, with a graphical representation provided in Fig. 6. The improved SegNet model integrates DenseNet's dense connectivity, which facilitates better feature reuse and multi-scale information extraction. As a result, it demonstrates superior performance, achieving improvements in precision, recall, and Dice coefficient of 3.49%, 3.34%, and 2.35%, respectively, over the original SegNet. These enhancements are attributed to the integration of DenseNet's dense connectivity, which facilitates better feature reuse and multi-scale information extraction. Regarding Recall, which measures the model's ability to correctly identify all relevant instances, improved SegNet outperformed U-Net, FCN, and SegNet by 3.15%, 5.93%, and 3.34%, respectively. Specificity, which indicates the model's ability to correctly classify background pixels, also showed slight improvements with improved SegNet, with increases of 0.31%, 0.53%, and 0.76% over U-Net, FCN, and SegNet, respectively. The Dice coefficient, a similarity measure comparing the segmented output to the ground truth, showed that improved SegNet achieved higher similarity scores, with improvements of 1.98%, 3.69%, and 2.35% over U-Net, FCN, and SegNet. The increase in Dice coefficient suggests that the improved model is able to produce more accurate segmentation outputs, due to its capability to retain multi-scale semantic information through the reuse of feature maps from various layers.

TABLE II
COMPARISON OF ACCURACY EVALUATION INDEXES FOR SEGNET, U-NET, FCN AND OUR MODEL.

Model	Precision(%)	Recall(%)	Specificity(%)	Dice(%)
SegNet	81.83	80.36	80.51	81.25
U-Net	79.15	78.72	78.81	79.06
FCN	80.73	79.94	80.15	80.37
Improved SegNet	85.32	83.87	84.36	84.81

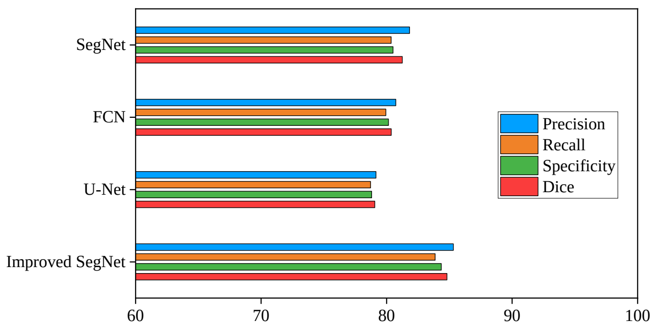


Fig. 6. Comparison of segmentation accuracy among different models

Improved SegNet connects and reuses feature maps across different layers, facilitating the extraction of richer image features and improving segmentation precision. This feature reuse approach, inspired by DenseNet, enables the model to better capture and retain critical semantic information across scales, mitigating the information loss typically seen in the original SegNet. In addition to accuracy, the recognition success rate of damage points was evaluated by analyzing the total number of correctly identified damage points across all the armor images. Of the total 425 damage points, SegNet correctly identified 387, while improved SegNet identified 402. Thus, the recognition success rates for SegNet and improved SegNet were 91.06% and 94.59%, respectively, showing a 3.53% improvement with the enhanced model.

The improved SegNet model maintains computational efficiency comparable to the original SegNet, with only a marginal increase in processing time. This makes it suitable for real-time applications: battlefield damage assessment, where rapid processing is essential. This is evident from the computational statistics shown in Table 3. FCN, with its fully connected layers converted into convolutional layers, demonstrates much slower training speeds. Moreover, their forward and backward pass times are comparable to, or even exceed, those of SegNet. Notably, overfitting is not a major issue when training these larger models, as their performance metrics tend to improve over iterations, similar to SegNet. For FCN, learning transposed convolutional layers, rather than relying on bilinear interpolation weights, can enhance performance. This modification also allows the model to achieve better metrics within a shorter time frame. Interestingly, the trained U-Net achieves competitive performance despite being the least parameterized model with the fastest training time, as shown in Table 3. However, U-Net struggles with lower segmentation accuracy when compared to its counterparts.

TABLE III
COMPARISON OF COMPUTATIONAL TIME AND HARDWARE RESOURCES REQUIRED FOR SEGNET, U-NET, FCN AND OUR MODEL.

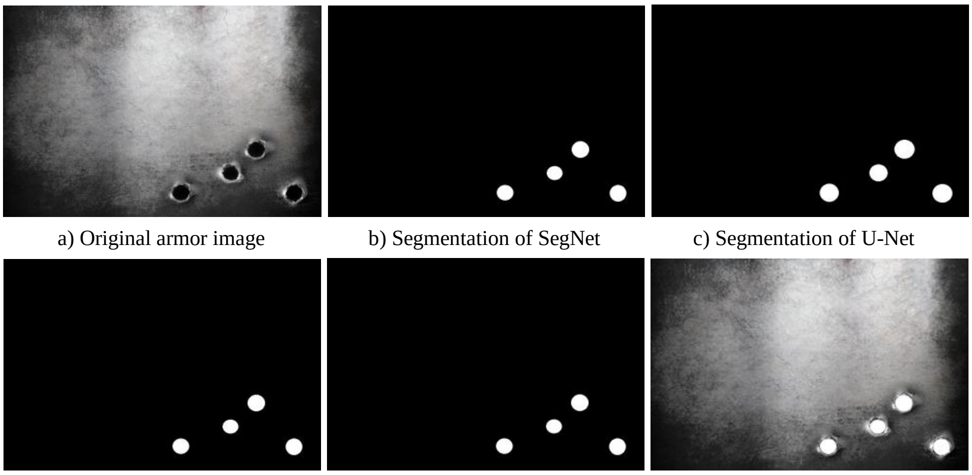
Model	Forward Pass (ms)	Backward Pass (ms)	GPU Traning Memory (MB)	GPU Inference Memory (MB)	Model Size (MB)
SegNet	381.83	380.36	6805	1081	135
U-Net	179.15	178.72	5788	1979	94
FCN	350.73	379.94	8480	1880	572
Improved SegNet	385.32	383.87	6843	1084	137

After a period of training, improved SegNet surpasses other networks in terms of segmentation accuracy. This subtle yet crucial difference in runtime emphasizes improved SegNet’s ability to achieve superior accuracy without a significant increase in processing time. By maintaining computational efficiency while delivering enhanced segmentation performance, improved SegNet demonstrates its robustness and practical applicability in battlefield environments.

C. Recognition performance on different armor types

In complex battlefield scenarios, accurate segmentation and identification of armor damage points are crucial for evaluating armor resilience. In this study, we applied SegNet, U-Net, FCN, and our model to recognize and segment damage points across various armor types, including multi-layer, single-layer, and composite armor. The comparative segmentation effects of these models on different armor types are shown in Fig. 7–9.

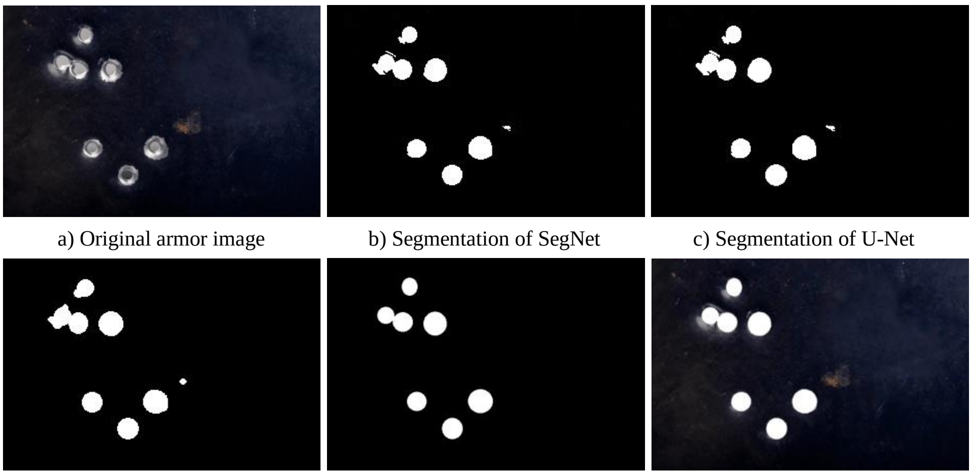
In the segmentation of multi-layer armor images, U-Net demonstrated inferior performance compared to the other models. Specifically, U-Net incorrectly identified some undamaged armor material as damage points, resulting in an overestimation of the damage areas. Fig. 8 and Fig. 9 reveal the segmentation limitations of SegNet. When SegNet, U-Net, and FCN were directly applied to single layer armor and composite armor images, segmentation errors occurred, resulting in inaccuracies in damage point detection. These challenges likely arise from SegNet's limited multi-scale feature extraction capabilities, which impact its ability to accurately detect fine details inherent in various armor compositions. When analyzing complex structures like composite armor, SegNet struggled to accurately distinguish between damage points and the surrounding material. Improved SegNet model, however, effectively addresses these issues by incorporating a more sophisticated approach to multi-scale feature utilization. Drawing from DenseNet model structure, this improved version enhances the connections between feature maps across different network layers. As a result, it allows for multiple reuses of image features, thereby improving segmentation precision.



a) Original armor image b) Segmentation of SegNet c) Segmentation of U-Net

d) Segmentation of FCN e) Segmentation of Improved SegNet f) Reconstruction effect

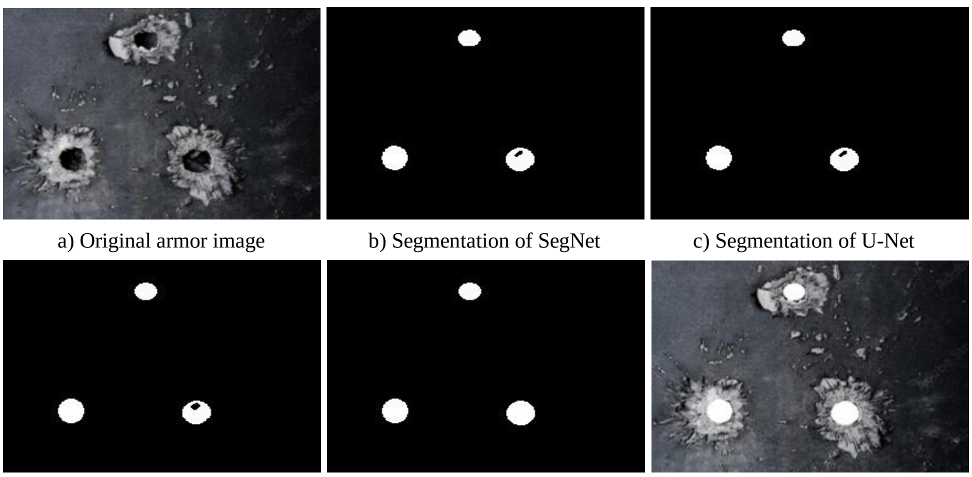
Fig. 7. Segmentation of multi-layer armor



a) Original armor image b) Segmentation of SegNet c) Segmentation of U-Net

d) Segmentation of FCN e) Segmentation of Improved SegNet f) Reconstruction effect

Fig. 8. Segmentation of single layer armor



a) Original armor image b) Segmentation of SegNet c) Segmentation of U-Net

d) Segmentation of FCN e) Segmentation of Improved SegNet f) Reconstruction effect

Fig. 9. Segmentation of composite armor

Improved SegNet demonstrates a significant reduction in segmentation errors, providing more clearly defined boundaries for damage points in both single-layer and composite armor images. This improvement is crucial for precise damage assessment, as it helps differentiate between closely situated damage points and noise. In the segmentation of composite armor, our model demonstrates enhanced robustness. This is particularly evident in situations where the layered material composition obscures or fragments damage point features. The ability of improved SegNet to retain critical information from multiple layers enhances its capacity to deliver consistent segmentation results across various armor types. As a result, this consistency is a key advantage in battlefield applications, where rapid and accurate assessment of armor damage is vital for operational decision-making.

IV. Discussion

While increasing model depth and parameter complexity can enhance performance, it is crucial to balance these factors with computational efficiency, especially in real-time applications. Future research will focus on developing more efficient architectures that maintain high accuracy while reducing computational overhead. However, in practical applications, selecting an appropriate model involves balancing multiple factors, such as memory consumption and computational time during both training and testing. These considerations impose critical constraints on deployment. Notably, as demonstrated in this study, when performance improvements are disproportionate to increases in training time, training efficiency becomes a key factor. Additionally, for tasks like armored damage detection, memory requirements and computational load during the testing phase are equally critical, especially in battlefield environments where real-time responsiveness is essential. Compared to other competing architectures, improved SegNet achieves excellent performance, similar model size, and runtime in armor damage analysis.

When benchmarking segmentation architectures with different parameter configurations and depths, the choice of training method is crucial. Many architectures rely on auxiliary techniques and multi-stage training methods to achieve high accuracy, complicating the assessment of their true performance under time and memory constraints. To address this, our study integrates direct connections between feature maps across different network layers, allowing multiple feature reuse. This modification enhances inter-layer feature propagation, addressing the limited multi-scale capability of SegNet. However, it is important to note that this approach cannot entirely isolate the interactions between the model architecture and the solver in achieving specific outcomes. Training deep networks inherently involves imperfect gradient backpropagation and optimization challenges associated with high-dimensional non-convex problems. Therefore, this controlled analysis complements other benchmarks, highlighting practical trade-offs among well-known architectures.

Looking ahead, our research team plans to leverage insights from this benchmarking study to design more efficient architectures for real-time applications. Additionally, we are interested in exploring methods for evaluating the uncertainty of predictions in deep segmentation architectures, a key focus of future work.

V. Conclusions

This study enhanced the accuracy of damage point detection in segmented armor images using a battlefield-collected dataset, with SegNet as the base architecture. Recognizing SegNet's limitations in utilizing multi-scale information, we improved the model by incorporating DenseNet-inspired modifications, which establish direct connections between feature maps across different layers. This modification enables more efficient feature reuse, improving inter-layer feature propagation and mitigating SegNet's limitations in multi-scale capabilities.

Improved SegNet was evaluated against SegNet, U-Net, and FCN on various armor types, including multi-layer, single-layer, and composite armor. Quantitative evaluation showed significant improvements: precision increased by 3.49%, recall by 3.34%, specificity by 0.76%, and Dice coefficient by 2.35%, indicating enhanced segmentation accuracy and reduced false positives.

These improvements have significant practical implications for battlefield applications, where accurate damage assessment is crucial for timely decision-making. The model's improved ability to distinguish damage points across diverse armor types provides more reliable results, addressing challenges posed by varying armor structures. Improved SegNet achieved a recognition success rate of 94.59%, compared to SegNet's 91.06%. The processing time for 100 images showed a negligible increase, while maintaining operational efficiency. By integrating multi-layer feature maps, improved SegNet provides precise, reliable results, making it an effective tool for real-time armor damage assessment and advancing damage detection technologies in military and engineering applications.

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