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# Deep Learning-Based Detection and Classification of Blunt Abdominal Trauma

Huawei Lin [1, *], Zeyuan Zhang [2], Longlong Zou [3], Chunlei Yang [1]

[1] College of Information Engineering, Henan University of Science and Technology, Luoyang, China

[2] College of Software, Henan University of Science and Technology, Luoyang, China

[3] College of Mathematics and Statistics, Henan University of Science and Technology, Luoyang, China

*Corresponding Author: Huawei Lin

## ABSTRACT

Traumatic injuries are the leading cause of death in the first four decades of human life and represent a major global public health issue. It is estimated that over 5 million people die from traumatic injuries each year worldwide. Among these, blunt abdominal trauma (BAT) accounts for approximately 75% of all blunt injuries, making it the most common type. However, in the early stages, there may be few or no obvious signs indicating serious intra-abdominal injuries, which makes assessment particularly challenging and requires a high index of clinical suspicion. In such cases, accurate and timely diagnosis of traumatic injuries is crucial. According to extensive literature research, traditional medical image classification methods often rely on manually designed feature extraction and classifiers. These methods tend to perform poorly when dealing with complex medical images. In contrast, deep learning techniques, based on end-to-end learning, can automatically learn feature representations and classification models directly from raw image data, offering better generalization performance than traditional approaches. Furthermore, there is currently a lack of computer-aided diagnosis (CAD) systems specifically designed for the detection and classification of CT images related to blunt abdominal trauma (BAT). Based on this observation, this study proposes the development of a deep learning-based CAD system aimed at supporting the diagnosis and classification of CT images for BAT.

## KEYWORDS

Deep learning; Blunt abdominal trauma detection; Computer-aided diagnosis and treatment system; Image detection; Image classification

## 1. INTRODUCTION

Blunt Abdominal Trauma (BAT) is one of the most common types of abdominal injuries. The primary causes include traffic accidents (accounting for approximately 61%), interpersonal violence (around 24%), and falls (about 7%) [1, 2]. In such trauma cases, multiple vital organs within the abdominal cavity—such as the liver, spleen, kidneys, and intestines—may suffer varying degrees of damage, potentially leading to serious complications like internal bleeding and organ dysfunction, posing a direct threat to the patient's life. Among these, liver and splenic injuries are particularly common, together accounting for approximately 70% of visceral injuries [3, 4].

In clinical practice, while prompt intervention is required for trauma that significantly affects solid organs, the majority of BAT cases are managed conservatively through Non-Operative Management

(NOM). This strategy has been shown to reduce trauma-related morbidity and mortality, with numerous studies demonstrating its effectiveness in minimizing the risks associated with invasive procedures [5, 6].

With the decline in the use of diagnostic peritoneal lavage, the diagnosis of BAT now primarily relies on high-resolution imaging examinations, especially Computed Tomography (CT) scans. As the "gold standard" for trauma diagnosis, CT scanning provides high-quality images that clearly show pathological changes in abdominal organs (such as the liver, spleen, pancreas, kidneys, etc.), including lacerations, contusions, and hematomas [7, 8]. However, the interpretation of CT images heavily depends on experienced radiologists, which makes the diagnostic process highly subjective and susceptible to misdiagnosis or missed diagnosis. Moreover, this situation highlights the imbalance in medical resource distribution [9, 10].

In recent years, deep learning techniques have achieved remarkable progress in the field of image analysis. Convolutional Neural Networks (CNNs) have demonstrated outstanding performance in tasks such as image classification, object detection, and segmentation [11-13], and are increasingly being applied to medical image analysis [14, 15]. By using deep neural networks to learn features from CT images, it is possible to automatically extract highly discriminative high-level semantic information from large-scale data, thereby improving the recognition of trauma regions and injury severity. At the same time, Multi-Task Learning (MTL) frameworks enable joint optimization for different injury types by sharing low-level network features, effectively enhancing model generalization and detection performance [16, 17].

Based on the above background, this paper proposes a multi-task deep learning model that integrates an efficient feature extraction network and an attention mechanism [18] to achieve automatic detection and intelligent classification of blunt trauma in abdominal CT images. By incorporating EfficientNet-B0, CBAM (Convolutional Block Attention Module), and a weighted focal loss to address class imbalance, the proposed model aims to accurately locate and classify injuries to major abdominal organs, providing an efficient and accurate computer-aided diagnostic tool for use in emergency clinical settings.

The remainder of this paper is organized as follows: Section 2 reviews related work; Section 3 presents the proposed model and methodology; Section 4 details the experimental setup and results; and finally, Section 5 concludes the paper with a summary and discussion.

## 2. RELATED WORK

In recent years, deep learning has made significant progress in the field of medical image analysis. Compared to traditional classification methods that rely on handcrafted features, its end-to-end feature learning capability demonstrates clear advantages in both performance and adaptability. Deep learning has been widely applied to key tasks such as lesion detection, organ segmentation, disease classification, and prognosis assessment across multiple imaging modalities, including MRI, CT, and ultrasound [19].

Sogancioglu et al. [20] proposed an early lung cancer diagnosis system based on CT imaging, consisting of two modules: segmentation and classification. These modules were developed using the UNETR architecture and a self-supervised learning network, respectively. The method achieved excellent performance on public datasets, with a segmentation accuracy of 97.83% and a classification accuracy of 98.77%. Liu et al. [21] introduced a weakly supervised learning method aimed at improving the specificity of binary classification of breast MRI lesions. They constructed a model based on ResNet-101 and used softmax scores (with a threshold of 0.5) to determine the malignancy of lesions, achieving a classification accuracy of 94.2% on the validation set. Fu et al. [22] proposed an automatic segmentation approach for medical images used in cardiac modeling by

leveraging U-Net and Transformer architectures. Their method improves segmentation accuracy by extracting and modeling features at multiple scales.

In the field of abdominal trauma diagnosis, existing studies mostly focus on the extraction and utilization of traditional CT imaging features [23]. For example, Ganesan et al. [24] input CT images into a convolutional neural network (CNN) to detect blunt abdominal trauma, achieving promising preliminary results. However, such methods are mostly limited to single-organ modeling, such as the classification and identification of liver injuries [25]. These approaches are insufficient for handling complex clinical scenarios involving multiple concurrent organ injuries.

## 3. METHOD

In this study, we propose a deep convolutional neural network model based on a multi-task learning (MTL) framework for abdominal injury detection [26]. As illustrated in Fig. 1, the model leverages features from a pretrained backbone and integrates attention mechanisms along with task-adaptive loss design to enable joint learning and discrimination of multiple tasks. This design significantly enhances the detection performance for injuries across different abdominal organs.

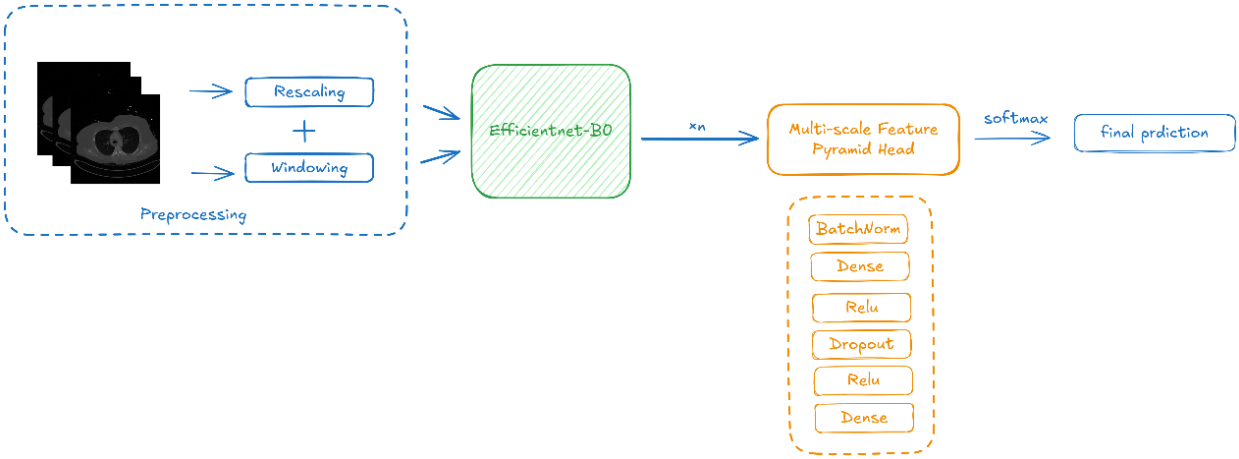


**Figure 1.** The overall pipeline of our attack method

To fully leverage the representation power of pretrained models, this study adopts EfficientNet-B0 as the backbone network [27]. Since the input data consists of single-channel grayscale images, the first convolutional layer of the original model, which expects three-channel input, is modified to accommodate single-channel inputs. This adjustment ensures the effective transfer of pretrained weights.In addition, to prevent overfitting of low-level features during training, the first four layers of the backbone network are frozen, allowing only the later layers to be updated. This strategy enhances the generalization capability of the model.

### 3.1. Attention Enhancement Module

Following the basic feature extraction module, this study introduces the Convolutional Block Attention Module (CBAM) to further enhance feature representation capabilities [28]. The module first captures global semantic information via global average pooling and global max pooling, and obtains a channel attention map using fully connected layers. Next, a spatial attention mechanism is applied to the channel-weighted features for adaptive recalibration in the spatial domain. Specifically, the CBAM module utilizes the statistical information obtained by the two pooling methods, which is then nonlinearly mapped through a set of shared fully connected layers, followed by the application of a Sigmoid activation function to generate the attention coefficients. Ultimately, the module applies both channel and spatial attentions to the input feature map, achieving dual modulation of the feature representation and enabling the model to more precisely focus on the local regions and key semantic

information closely related to abdominal injuries. Given an input intermediate feature map $F$, the process can be summarized by the following formula:

$$\mathrm{F}' = \mathrm{M_c}(\mathrm{F}) \otimes \mathrm{F} \tag{1}$$

$$\mathrm{F}'' = \mathrm{M_s}(\mathrm{F}') \otimes \mathrm{F}' \tag{2}$$

Where $M_c$ denotes the channel attention module, and $M_s$ represents the spatial attention module. The formulation of $M_c$ is detailed below:

$$\mathrm{M_c}(\mathrm{F}) = \sigma(MLP(AvgPool(\mathrm{F})) + MLP(MaxPool(\mathrm{F}))) \tag{3}$$

Where $\sigma$ denotes the sigmoid function, MLP refers to a multi-layer perceptron neural network, and AvgPool and MaxPool represent average pooling and global pooling, respectively.

The calculation of $M_s$ is given as follows:

$$\mathrm{M_s}(\mathrm{F}) = \sigma(\mathrm{f}^{7\times7}([\mathrm{AvgPool}(\mathrm{F}); \mathrm{MaxPool}(\mathrm{F})])) \tag{4}$$

Where $\sigma$ represents a convolution operation with a 7×7 kernel.

### 3.2. multi-Task Classification Head

Considering that damage detection tasks for different organs exhibit varied class distributions and feature requirements, the model adopts a task-branch based multi-task learning strategy. After feature extraction and attention enhancement, high-dimensional features are mapped to low-dimensional representations via adaptive pooling and fully connected layers. For each task (including bowel, extravasation, kidney, liver, and spleen), independent multi-scale pyramid classification heads are designed [29]. Mapping the low-dimensional features back into a high-dimensional space enables the model to capture additional information.

Furthermore, to address the class imbalance issue inherent in different tasks, this study incorporates Focal Loss [30] and applies class-level weighting based on the data distribution. In addition, to ensure the losses from the various tasks converge harmoniously, GradNorm [31] is introduced. GradNorm adds an auxiliary gradient loss on top of the main loss—the main loss is responsible for updating the network parameters, while the gradient loss updates the sample weights.

For each task $t \in T$, the loss is computed as follows:

$$\mathcal{L}_t = -\alpha * (1-p)^\gamma * y * log(p) - (1-\alpha) * p^\gamma * (1-y) log(1-p) \tag{5}$$

Where $\alpha$ denotes the weight for positive samples, $p$ represents the probability that the model predicts the sample as positive, and $\gamma$ is the modulating factor for sample difficulty. Then, the total loss $\mathcal{L}_{\mathrm{total}}$ is defined as:

$$\mathcal{L}_{\mathrm{total}} = \sum_{t=1}^{T} w_t \mathcal{L}_t. \tag{6}$$

Where $w_t$ represents the weight assigned to task t.

# 4. EXPERIMENTS

Our model was trained using 5-fold cross-validation with the AdamW optimizer. The initial learning rate was set to 2e-5, and a cosine decay scheduler was employed. Early stopping was triggered if the validation loss did not improve for 5 epochs. The model was trained for 10 epochs using a single Nvidia 4090 GPU (24GB memory), with a batch size of 512 and an input image resolution of 224×224. Each epoch of training took approximately 10 minutes. For the focal loss function, the weight parameter $\alpha$ was set to 0.25 and the focusing parameter $\gamma$ was set to 2.

## 4.1. Datasets

The RSNA Abdominal Trauma CT (RATIC) dataset is currently the largest publicly available dataset of adult abdominal CT examinations, focusing on the automatic detection and grading of traumatic injuries [32]. This dataset covers trauma detection and classification tasks for multiple key organs, including the liver, spleen, kidneys, intestines, and mesentery. All annotations were rigorously completed by experienced radiology experts from the American Society of Emergency Radiology (ASER) and the Society of Abdominal Radiology (SAR), ensuring authoritative and high-quality labeling. The dataset provides multi-level, multi-dimensional annotation information. For three major solid organs, the dataset not only labels the presence or absence of traumatic injuries but also records detailed injury grading, thus providing fine-grained supervisory signals for the model. In addition, at the image level, key pathological features such as active extravasation and bowel injury are specially annotated, aiding in the rapid identification of cases requiring immediate intervention. Furthermore, the dataset offers voxel-level segmentation annotations of potentially injured organs, enabling precise localization and quantitative analysis based on segmentation, thereby providing strong support for subsequent lesion detection and treatment planning.

In this study, we first preprocessed the original CT images using metadata information from DICOM-standard files. The raw pixel values were linearly calibrated to Hounsfield units, and necessary corrections were performed on pixel representations acquired under different imaging parameters. Next, a gray-level truncation method based on window width and window level was applied to effectively suppress non-diagnostic signals while standardizing the image intensities. To ensure spatial consistency across images while also considering computational complexity, all images were resampled to a preset resolution using bilinear interpolation. Given the variability in slice thickness in the original data, we further utilized the relevant parameters from the DICOM files and applied a sampling strategy to standardize the slice thickness. The processed images demonstrate high diagnostic sensitivity.

## 4.2. Evaluation Metric

To comprehensively evaluate the performance of the proposed model in the task of detecting and classifying blunt abdominal trauma, this study introduced multiple evaluation metrics, primarily including accuracy, F1-score, and AUC.

Accuracy; Accuracy measures the model's overall prediction correctness across all task samples. This study involves binary or multi-class detection for multiple organs (e.g., bowel, extravasation, kidney, liver, spleen). As an intuitive metric, accuracy reflects the model's overall discriminative ability. Although it is sensitive to class imbalance, it can still serve as a reference for performance evaluation when combined with other metrics.

F1-score; To address class imbalance issues, the F1-Score was adopted for evaluation. This metric independently calculates the precision and recall for each class, takes their harmonic mean, and then computes the unweighted average across all classes, ensuring equal weighting for every category in the assessment. This approach helps improve the model's performance in detecting minority-class injuries, making it particularly suitable for high-sensitivity tasks such as medical imaging analysis.

AUC; The AUC reflects a model's classification stability and discriminative ability across different decision thresholds, serving as a key indicator of generalization performance. For binary classification tasks (e.g., bowel and extravasation), the AUC value is directly computed for the positive class. For multi-class tasks (e.g., kidney, liver, and spleen), a one-vs-rest (OvR) strategy is employed, where the AUC is calculated separately for each class and then aggregated via macro-averaging. The AUC effectively reveals the model's sensitivity in distinguishing between different injury severity levels, offering high clinical relevance—especially in medical decision-support scenarios requiring stringent risk control.

### 4.3. Main Results

In this experiment, we conducted a systematic evaluation of the proposed model's classification performance across different tasks, with the results summarized in Table 1. Overall, all tasks achieved an AUC above 0.82, indicating the model's strong discriminative ability in distinguishing between normal and damaged conditions. The overall AUC reached $0.836 \pm 0.009$, further demonstrating the model's robustness in the multi-organ joint learning setting.

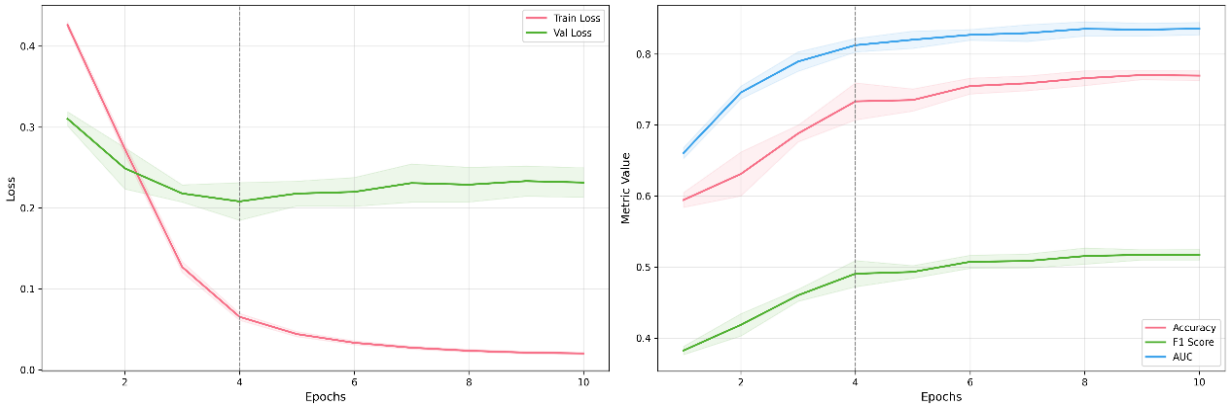


**Figure 2.** The left panel shows the trend of training and validation loss as the number of epochs increases, while the right panel illustrates the changes in the three metrics Accuracy, F1 score and AUC with increasing epochs.

Specifically, the AUCs for Bowel and Spleen were both close to 0.84, suggesting relatively clear decision boundaries for these types of injuries. For Extravasation (active bleeding), the model achieved an F1-score of $0.615 \pm 0.016$ and the highest accuracy of $0.815 \pm 0.025$, highlighting its sensitivity in capturing such lesion features. Additionally, the model maintained high AUC values for Kidney and Extravasation ($0.834 \pm 0.018$ and $0.834 \pm 0.008$, respectively), indicating its capability to extract discriminative features even for more complex or less well-defined injury types.

Overall, the model demonstrated promising detection performance across all five tasks, with stable metrics and good generalizability, providing strong support for multi-organ abdominal injury detection and diagnosis.

Fig. 2 illustrates the overall trend of validation AUCs across folds for each task under five-fold cross-validation. It can be observed that all tasks maintain relatively high AUC levels (approximately between 0.80 and 0.90) across different folds, indicating a certain degree of robustness in multi-organ injury recognition.

Specifically, Bowel and Extravasation exhibit relatively stable performance across most folds, with slightly higher AUCs in many cases, suggesting more consistent discriminative ability for intestinal and bleeding-related injuries. In contrast, Liver and Kidney show noticeable fluctuations between folds, which may be attributed to differences in sample distribution and the diverse characteristics of lesions. Spleen demonstrates an overall steady trend—though slightly lower than other tasks in some folds, it still remains within a reasonable performance range.

**Table 1.** Performance Metrics for Each Task

| Task | Auc (Mean+Std) | F1-Score (Mean+Std) | Accuracy (Mean+Std) |
|---|---|---|---|
| Bowel | 0.846±0.015 | 0.517±0.004 | 0.794±0.007 |
| Extravasation | 0.834±0.008 | 0.615±0.016 | 0.815±0.025 |
| Kidney | 0.834±0.018 | 0.476±0.027 | 0.787±0.021 |
| Liver | 0.827±0.012 | 0.481±0.011 | 0.735±0.012 |
| Spleen | 0.838±0.011 | 0.500±0.005 | 0.717±0.004 |
| Overall | 0.836±0.009 | 0.518±0.008 | 0.770±0.007 |

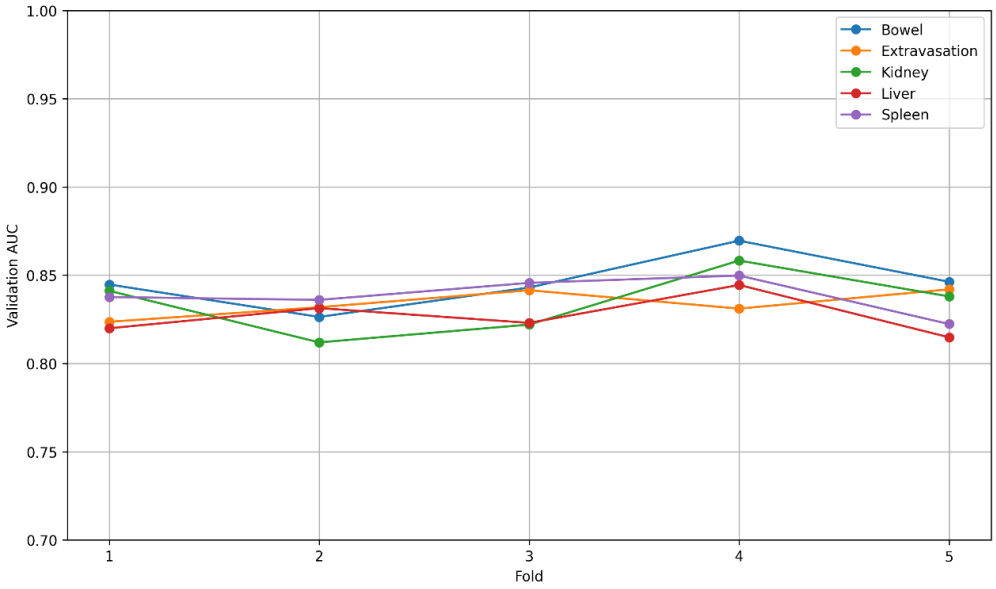


**Figure 3.** Visualization of validation AUCs for the five tasks Bowel, Extravasation, Kidney, Liver and Spleen under five-fold cross-validation.

Moreover, as shown in Fig. 3, the AUC values for all tasks increase with training epochs within the same fold, accompanied by similar upward trends in other key metrics such as Accuracy and F1-score. This further confirms the model's progressive performance improvement during training and its ability to achieve coordinated enhancement across multiple evaluation dimensions.

## 5. SUMMARY

In this study, we propose a deep convolutional neural network model based on a multi-task learning framework to assist in the diagnosis and classification of Blunt Abdominal Trauma (BAT) using CT images. The model is built upon EfficientNet as the backbone and incorporates a multi-task pyramid-structured classification head, enabling joint prediction of multiple tasks and allowing the identification of various injury types within a single training process. To further optimize the multi-task training, we introduce the GradNorm algorithm to dynamically adjust gradient weights across tasks, achieving adaptive balance among them. Experimental results demonstrate that the proposed model framework achieves strong performance in BAT detection and classification tasks, showing high potential for clinical application.

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