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AI-Powered Imaging: Deep Learning in Trauma Radiology

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Abstract

Diagnostic imaging plays a critical role in contemporary trauma care for preliminary assessment and detection of injuries that need intervention. Deep learning (DL) has gained mainstream application in medical image analysis and has demonstrated excellent efficacy for classification, segmentation, and lesion detection. This narrative review offers the underlying principles on creating DL algorithms in trauma imaging and offers an overview of recent developments in each modality. DL has been applied to detect free fluid on Focused Assessment with Sonography for Trauma (FAST), traumatic findings on chest and pelvic X-rays, and computed tomography (CT) scans, identify intracranial hemorrhage on head CT, detect vertebral fractures, and identify injuries to organs like the spleen, liver, and lungs on abdominal and chest CT. Future directions involve expanding dataset size and diversity through federated learning, improving the model explainability and transparency, which also would increase the clinicians' trust in the model, and in multimodal data to offer more meaningful insights into traumatic injuries. Although some commercial AI products are approved by the Food and Drug Administration for clinical use in the trauma field, yet the adoption is quite low, which calls for multi-disciplinary teams to engineer practical, real-world solutions. In general, DL demonstrates vast potential to enhance the effectiveness and accuracy of trauma imaging, but careful development and verification are essential to guarantee these technologies benefit patient care.

Keywords : Deep learning, Artificial intelligence, Medical image, Trauma, Radiology, Computed Tomography

Introduction

In modern trauma care, various imaging modalities are essential, especially for patients with blunt trauma. Although there are situations in which patients require immediate surgical investigation, diagnostic imaging offers clinicians useful information that opens the door to endovascular and non-operative management and therapies. Key imaging modalities for initial evaluation include chest and pelvic X-rays, the Focused Assessment with Sonography for Trauma (FAST), and computed tomography (CT) scans focusing on the head and cervical spine. For areas of suspected injury, targeted CT imaging is frequently indispensable for making precise diagnoses. The use of whole-body CT scanning has grown increasingly common for evaluating trauma patients with polytrauma or high-risk injury mechanisms, offering comprehensive diagnostic insights quickly to inform management decisions. In the fast-paced environment of trauma care, clinicians are often tasked with interpreting numerous imaging results, sometimes in the absence of a radiologist's direct input. Moreover, emergency radiologists encounter distinct challenges in a high-stakes environment where time and safety are critical [1].

Deep learning (DL) is a machine learning algorithm based on artificial neural networks that have developed very rapidly over the past ten years, emerging today as one of the primary algorithms to support computer vision and natural language processing, which describes artificial intelligence (AI) more recently. DL has myriad applications within medical imaging. These include disease classification in chest radiography, lesion detection in chest CT scans, mammography interpretation, and Analysis of brain MRI images [2]. DL has also been used to segment lesions and organs in brain CT [3] and abdominal CT scans [4]. In trauma imaging, the recent scoping review points to increasing DL applications in CAD for trauma [5]. We provide here a narrative review that encompasses a complete foundational overview of DL. Which are crucial for guiding the development of medical DL projects. We explore the current applications of DL in trauma imaging and discuss potential avenues for future advancements.

Fundamental concepts of deep learning

The basic concept of artificial neural networks was proposed as early as the 1960s, inspired by the biological nervous system as a machine learning algorithm. The architecture consists of multiple artificial neurons connected by weighted connections (perceptron), forming a hierarchical structure typically comprising input, hidden, and output layers. Each connection between neurons involves a mathematical computation that increases the computation requirement as neurons and layers increase, which limits its development and utilization in the early years. However, with advancements in computational capabilities, particularly the advent of graphic processing units (GPUs) utilized in the computation of neural networks in early 2010 [6], developing deeper network structures of neural networks became possible. "Deep learning' is predominantly employed to describe such multilayered neural networks, thereby superseding the earlier nomenclature of multilayer neural networks.

Before the advent of DL, the dominant image analysis approach employed hand-crafted feature selection feature extraction and subsequent machine learning methods. Designing a convolutional neural network (CNN) basically breaks the idea and uses an end-to-end algorithm framework that automatically learns the features in the training phase. This strategy quickly became the primary image analysis method upon obtaining remarkable success in ImageNet competition [7] and became a cornerstone in DL.

While DL techniques have succeeded considerably in natural image classification, researchers have tried to adapt them to medical images. Training a robust DL model from scratch requires extensive volumes of image data, principally due to the high-dimensional feature space inherent to these algorithms. However, the collection of medical images is more challenging than natural images. Fortunately, the concept of "transfer learning' allows for fine-tuning pre-existing DL models on new image datasets, thereby enabling the application of models initially trained on one domain of images to be effectively re-purposed for a distinct target domain [8]. Early successful works in medical imaging include retina images, skin lesions classification, chest radiography interpretation, digital pathology, and lung nodule detection [2]. The DL algorithm in the image analysis field is mainly categorized as classification, segmentation, object detection, registration, and image generation.

The classification algorithms, such as AlexNet, ResNet series, Inception series, DenseNet, ResNeXt, and VisionTransformer, are the basis of DL in computer vision [9]. The trained model can recognize the input images as a specific class if the class is defined during the training process. For example, the collected ankle radiography can be defined as "fracture" or "normal" to train an ankle fracture detection algorithm. Multiple class identification is also possible if the image number of each class is sufficient for training. Segmentation algorithms such as Fully Convolutional Network, U-Net, DeepLab series, and SegNet [10] can partition an image into multiple parts and contour the target object by pixel-wise classification. The segmentation algorithms can precisely identify the target lesion, for example, hemorrhage in a brain CT [3].

However, intensive annotation effort is needed to draw the target lesion contour in each training dataset to train a segmentation algorithm, making high-quality datasets rare. Object detection networks such as R–CNN, Faster R–CNN, YOLO series, RetinaNet, and Single Shot MultiBox Detector [11] are designed to identify the target object in the image and place a bounding box to point out the location. The training data can be prepared with rectangle boxes to define the lesion area without detailed contouring. An example of applying different algorithms for spleen injury detection in CT scans is shown in [Fig. 1]. Other techniques, such as registration and generation algorithms, might improve performance. Image registration proves to be an effective tool in terms of aligning the different modalities but accurately. For instance, Zhou et al. used this method to register the arterial phase and venous phase CT scans in order to continue with vascular injury segmentation [12]. Image generation algorithms are widely used as training data augmentation techniques in medical imaging.

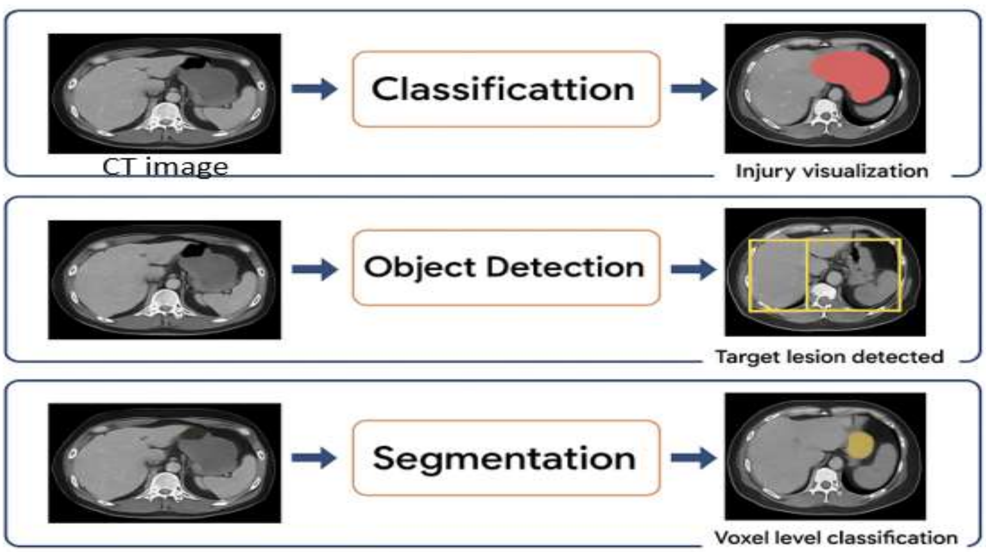

Figure: using several methods to identify damage to the spleen.

The most frequently used performance evaluation metric is the area under an operating characteristic curve (AUROC), which can be used to compare different models' performance in the same dataset because the model outputs are usually a probability value. After defining a cutoff value, the accuracy of diagnosing a specific injury by a binary class can be evaluated. However, the sensitivity (recall), specificity, positive predictive value (precision), and negative predictive value are much more critical to evaluating the true presentation of a model regarding the prevalence and the dataset imbalance [13]. The most commonly used evaluation indices in the segmentation algorithm include pixel accuracy, Intersection over union (IoU), and Dice similarity coefficient (DSC). Mean average precision (mAP) is specifically used in object detection algorithms to summarize prevision and recall across all object classes [14]. An independent or external test set is best for objectively evaluating the models because DL algorithms tend to overfit the training dataset. Researchers must avoid data leakage across training and test sets.

In medical imaging, some modalities, such as CT, should be interpreted through three-dimensional (3D) or dynamic approaches rather In comparison to relying solely on a single two-dimensional (2D) view, this process includes converting the pixel 2D images into a 3D dimension and adapting the algorithm to analyze the scans on a voxel basis. Although 3D techniques provide thorough insights, they need a significant amount of processing power. Additionally, a lot of DL methods are only partially convertible to 3D formats because they were first created for 2D picture analysis. A 2.5D technique has been used by some researchers to address this, which lowers computational requirements while improving analysis depth by including more spatial context from neighboring slices [15,16]. Provides an illustration of the distinction between developing splenic damage detection models using 2D or 3D algorithms. [Fig. 2]

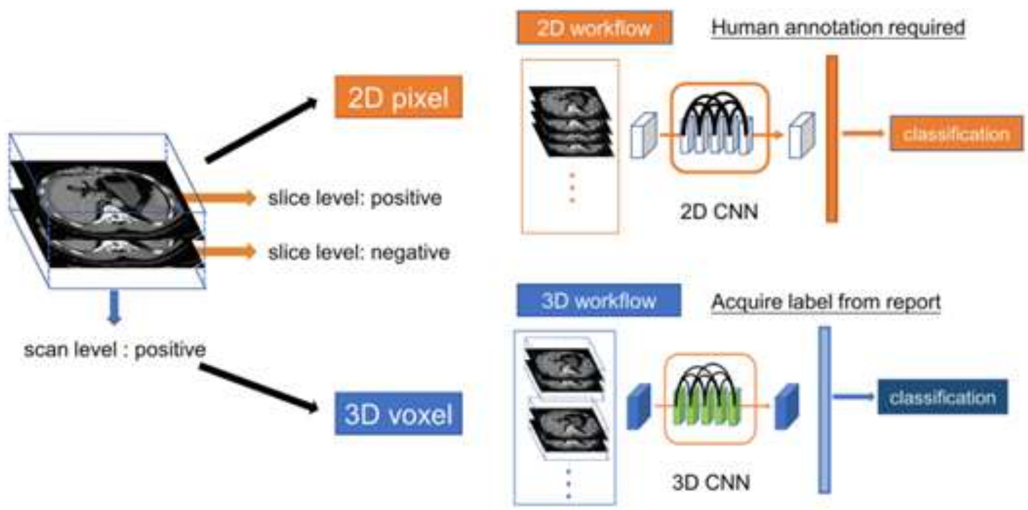

Figure 2 : An illustration of how 2D and 3D categorization algorithms differ in their workflow.

Medical institutions' DL model development follows a paradigm for assessing technology readiness for machine learning initiatives [17]. As shown in [Fig. 3], this broad prototyping workflow consists of a number of crucial components. First, the foundation of a particular project should be the expertise of professionals in the medical field. The majority of projects fail because the offered remedy is insufficient or has no therapeutic significance. Next, use your clinical knowledge and comprehension of a particular imaging modality to define the problem that needs to be solved. For instance, researchers might focus on a certain injury that is commonly misdiagnosed and has serious repercussions. The FDA defines the target application as either image processing/quantification (IPQ), computer-aided detection (CADe), computer-aided diagnosis (CADx), or computer-aided triage (CADt). The Institutional Review Board (IRB) must approve every clinical data and picture capture in order to assess ethical and privacy concerns with medical data. Following the aforementioned preparation, researchers can begin collecting data directly from the source, primarily from publicly available open datasets or an institution's Picture Archiving and Communication System (PACS) repository, and then proceed with the de-identification procedure. Before developing the algorithm further, the partnering computer scientist must consult with medical specialists on how to translate the query into a useful computer vision task, including object identification, segmentation, or classification. Hospital databases contain existing labels, such as radiology reports and clinical diagnoses. However, segmentation masks are frequently missing, and radiologists' reports of emergency plain radiographs may have errors ranging from 3 to 6% [18]. As a result, manual labeling is typically necessary [19,20]. Although researchers can stack DL layers from scratch to fit their particular requirements, there are situations where the method structure based on natural images can be immediately applied to medical concerns. At last, performance starts to improve as a result of model training and adjustment iterations.

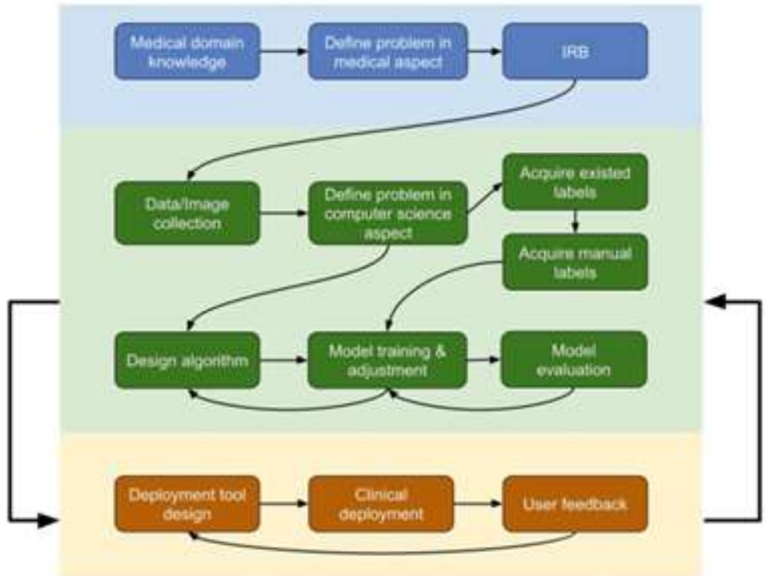

Figure 3: The process of creating a deep learning system for trauma imaging through prototyping. Institutional Review Board, or IRB.

Applications of deep learning in trauma imaging

An initial survey was conducted at the beginning of the trauma patient treatment workflow in order to quickly identify any life-threatening problems. A clinical workflow for a patient with significant abdominal bleeding is shown in [Fig. 4]. The Advanced Trauma Life Support (ATLS) guidelines recommend focused assessment with sonography in trauma (FAST) or extended FAST (eFAST) to examine the patient following the initial physical examination. Fast detection of hemoperitoneum or cardiac tamponade is the goal of the FAST exam, while eFAST includes chest exams to identify hemothorax or pneumothorax. Rough quantitative data, such as the volume of hemoperitoneum and hemothorax, might provide information on the severity of each targeted body region in addition to the exam's binary result. Using ResNet 50 and YoloV3, several research teams created free fluid detection models [21–23] that achieved over 95% accuracy in balanced datasets. Additionally, the DL algorithm has been tested by Chiu et al. to help beginners administer FAST tests. As a result, operators who receive AI advice have a higher mean acceptance score than those who do not (84% vs. 68%; P = 0.002) [24]. Taye et al. introduced a CNN autoencoder for evaluating the quality of ultrasound images, whereas Kornblith et al. automated view recognition in a pediatric sample using ResNet-152 [25]. Only Potter et al. used YoloV3 to identify pericardial fluid in chest trauma, with 78 instances showing 89% sensitivity [26]. Studies on the ultrasonography identification of traumatic pneumothorax or hemothorax are still lacking, though. The only attempt to train a CNN pneumothorax classifier in a synthetic tissue phantom was made by Boice et al.

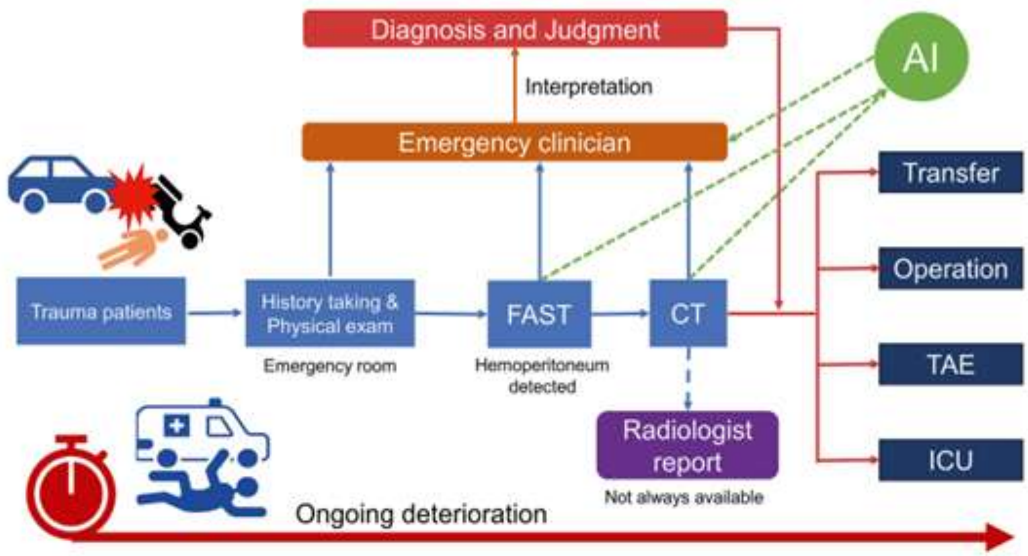

Figure 4: The clinical procedure for a patient who has internal bleeding and acute abdominal damage. The terms AI, CT, FAST, TAE, and ICU stand for artificial intelligence, computed tomography, focused assessment using sonography in trauma, and intensive care unit, respectively.

In the medical field, plain chest radiographs, also known as chest X-rays or CXRs, are the most widely utilized imaging modality. Numerous illnesses, including cardiomegaly, pneumonia, spontaneous pneumothorax, pleural effusion, tuberculosis [27], lung nodule or lung mass, etc., can be diagnosed using CXR [28, 29]. In order to identify rib fractures, hemothorax, pneumothorax, aortic injury, or other skeletal fractures, the CXR is also used as a first workup for trauma patients [30]. CXR is recommended for patients with multiple trauma, significant mechanism, or any thoracic symptom. Few studies have concentrated on trauma findings, despite the fact that there are numerous literature and even commercially accessible tools about the identification of medical disorders in CXR [31]. This may be connected to the fact that, with the exception of a small number of rib fractures, the majority of the publicly available large-scale open CXR datasets, including NIH ChestX-ray 14, CheXpert, MIMIC-CXR, PadChest, and VinDr-CXR, lack labels pertaining to trauma diseases [32]. The majority of research focuses on identifying rib fractures using private information because these are often overlooked conditions. Using benchmark networks, Huang et al. manually clip the rib region of interest in CXR in order to distinguish rib fractures from normal [33]. However, in the pediatric population, Ghosh et al. employ a patch-based sliding window strategy with a comparable methodology and the best AUROC of 0.89 [34]. On a limited number of CXR test sets, Sun et al. tested a straightforward framework for contrastive learning of visual representations, which produced the maximum sensitivity of 0.873 with five false positives per scan [35]. Other than the experimental method mentioned above, no compelling rib fracture detention model has been presented. Gipson et al. validated a commercially available CXR algorithm in trauma cases, and it performed better than radiologists in diagnosing pneumothorax and segmental collapse, but poorly in detecting clavicle, humerus, and scapula fractures [36]. None of the published articles addressed hemothorax, lung contusion, and great vascular damage, despite the fact that these are crucial findings in CXR. A number of crucial imaging modalities for trauma diagnosis are displayed in [Fig. 5].

Figure 5: (A) A chest X-ray reveals hemothorax and several fractures in the left ribs. (B) A pelvic fracture of the vertically shearing kind was seen on a pelvic plain film. (C) Several thoracoabdominal injuries were visible in a whole-body CT coronal scan. (D) Liver damage with active contrast extravasation is seen in an abdominal slice. (E) A CT scan of the chest showing a fractured right rib that is slightly displaced.

Pelvic radiographs (PXRs) are another plain film type that is advised for early examination in accordance with the ATLS guidelines in order to rule out pelvic fractures, which have the potential to cause severe bleeding. Additionally, this method can assess the hip and proximal femur to identify fractures in these regions. Hip fractures can be misdiagnosed in a busy emergency room, thus early management may prevent consequences in older persons. This makes hip fracture detection of major interest. A number of studies have created DL models with accuracy and sensitivity greater than 90% for the detection of hip fractures, including femoral neck and trochanteric fractures. [37–43]. Additionally, research has been done on the subclassification of hip fracture types [37,41,44]. Cheng et al. and Sato et al. discovered that the hip fracture detection model can help novice doctors improve diagnostic accuracy in addition to comparing the algorithm with humans [45,46]. Multiple-area pelvic fractures are more complicated when seen on a PXR. Cheng et al. created a universal detection system that detects pelvic fractures with 94.5% accuracy by combining DenseNet and feature pyramid networks. Nevertheless, the study's heatmap does not offer a high-level diagnostic classification; it merely shows the aberrant position [47]. Due to PXRs' intrinsic limitations in precisely identifying injuries in certain places, the accuracy of diagnosing specific fracture types, such as acetabular, sacral, and sacroiliac fractures, may be exaggerated. When it came to identifying fractures on pelvic images, an FDA-approved instrument had a sensitivity of 93.0% and a specificity of 91.5%. But there is not a thorough comparison of performance for various fracture forms [48].

The preferred picture for head trauma is a brain CT scan. Treating patients with severe brain damage requires prompt diagnosis of cerebral bleeding. Numerous research concentrated on cerebral hemorrhage associated with stroke, which can occasionally be difficult to differentiate from traumatic brain damage. Combining all cerebral hemorrhages, irrespective of the mechanisms, is another. To identify bleeding, the majority of research employ a slice-based strategy with classification and segmentation networks [49–51]. The performance ranges for sensitivity and specificity were 0.87 to 0.97 and 0.90 to 0.97, respectively. Chang et al. achieved an AUROC of 0.98 when they used a hybrid 3D/2D approach for bleeding detection and segmentation. Though their performances are inferior to pixel or image label datasets, integrating 3D-CNN could train models using inspection labels from large-scale datasets with fewer labeling efforts [52–54]. Different hemorrhage forms, including subdural, epidural, intraparenchymal, and subarachnoid hemorrhages, vary in severity. At the moment of identification, researchers also attempted to subtype the hemorrhage [55–57]. The best model had an AUC of 0.97 in a large-scale dataset [56], which may be prepared for clinical use even though model performance cannot be compared in the same dataset. It was also investigated how DL might be used to anticipate the results of brain damage. Pease et al. created a CNN and clinical model fusion model that performed better on external testing of the Transforming Research and Clinical Knowledge in Traumatic Brain Injury dataset but worse on internal data set mortality prediction, with an AUC of 0.92 [58]. 491 head CT scans with scan-level classification labels annotated by three radiologists for five different types of cerebral hemorrhage, the presence of calvarial fractures, midline shift, and mass effect are included in the open dataset CQ500 [51], which was made available in 2018. The Radiological Society of North America (RSNA) released a multi-institutional, international brain hemorrhage CT dataset in 2019 as part of their brain CT hemorrhage challenge. 874,035 photos from 25,312 exams make up this collection, which include slice-level classifications for five different forms of bleeding [59]. These datasets make it easier to benchmark freshly created algorithms for classification tasks.

To stop further deterioration, the C-spine damage should be recognized as soon as possible. Since the release of the 9th version of ATLS in 2012, C-spine CT has replaced plain film as the preferred preliminary diagnostic method. Plain films are used to look for thoracolumbar fractures, and a CT scan is used to confirm them. If the patient's condition permits, MRI should be used to further investigate spinal cord injuries. Naguib et al. used classification algorithms using a saliency map to assess C-spine fracture on lateral view radiographs [61], whereas Boonrod et al. looked into YOLO performance [60]. Some researches begin by segmenting the vertebrae on X-ray and CT images before immediately classifying damage cases [62–65]. Commercially available methods for detecting cervical spine fractures were examined by Voter et al.; the results showed a low sensitivity of 54.9% [66]. Ma et al. achieve a mean average precision of 88.6 when using Faster R-CNN to detect spinal cord damage on MRI [67].

CT scans of the chest, abdomen, and pelvis are frequently used to assess particular organ damage in trauma patients who are comparatively stable. CT becomes the gold standard for diagnosis and offers comprehensive information on organ integrity and body structures. For the detection of active bleeding, or contrast extravasation, contrast-enhanced CT is essential. CT provides useful information on the location, severity, and features of specific organ injuries, which helps doctors make decisions about prognosis and treatment options in an era where non-operative care and endovascular procedures are becoming more and more common [68]. In addition to aiding in hemopneumothorax quantification, chest CT also helps with the precise diagnosis of rib fractures, while CXR only offers approximations because of the interference of overlapping organs [69]. Moreover, CT is necessary for the precise definition of pelvic fractures, the identification of vascular injuries, and the provision of three-dimensional information for orthopaedic reconstruction [70]. WBCT scans, which enable definitive therapy despite greater radiation exposure, have been promoted more and more in recent decades as a quick way to assess patients with severe or multiple trauma and identify all potentially fatal injuries. Even radiologists and trauma surgeons must devote a significant amount of effort and expertise to interpreting the WBCT in these situations.

The gold standard for detecting damage to the heart, lungs, great vessels, and rib cage is chest CT. By introducing a RibFrac challenge in 2020 and offering a dataset of around 5000 rib fractures from 660 CT scans, the Medical Image Computing and ComputerAssisted Intervention (MICCAI) Society piqued researchers' curiosity [71]. Private or multicenter datasets were used in a number of subsequent studies [72] [–] [75]. Driezin et al. employed nn-Unet to obtain a mean Dice score of 0.67, while Choi et al. used 3D CNN to segment contused lung parenchyma and assess the severity among rib fracture patients. There was a correlation between the quantification results and clinical outcomes. In relation to major vessel injuries, Harris et al. created a 5-layer CNN to binary classify scans for aortic rupture and dissection, including traumatic aortic injury. They were able to achieve 100% and 96.0%

specificity for aortic rupture and 87.8% and 96.0% specificity for aortic dissection [76]. The stomach, gut, liver, spleen, pancreas, kidneys, and other solid and hollow digestive organs are all visible on abdominal CT.

In order to detect splenic injuries, Cheng et al. use 3D CNN and a two-step algorithm; their results show an AUROC of 0.901 with accuracy, sensitivity, and specificity of 0.88, 0.81, and 0.92, respectively [77]. However, because of the large degree of variation in AAST injury grading among doctors, the annotations were completed by a single trauma surgeon, which could introduce bias. AAST splenic damage grading was automated by Chen et al. using a four-part algorithm pipeline [78]. Regarding the differences in AAST grading agreement for blunt splenic injuries, the classification agreement (weighted κ) between automated and consensus AAST grades was 0.79, indicating a good performance [79]. In order to predict serious vascular injury, Dreizin et al. initially used a dilated-CNN segmentation technique in conjunction with attentional networks for CT volumetry on liver parenchyma, followed by decision tree analysis [80]. A straightforward U-Net method was also used by Farzaneh et al. to measure liver damage [81].

Clinical results are directly impacted by the stability, severity of pelvic fractures, and related vascular injuries that are appropriately assessed by pelvic CT scan [70]. Zapaishchykova et al. automatically classified translational and rotational instability using a Faster-RCNN model for fracture detection and Bayesian tile grade refining, obtaining AUCs of 0.833 and 0.851, respectively [82]. Alternately, Dreizin et al. performed similarly to radiologists by using an LSTM RNN network in conjunction with a ResNeXt-50 backbone to identify translational and rotational instability. The model's detection of translational instability was further linked to the requirement for heavy transfusion and TAE [83]. The use of these methods may make it possible to identify patients who are at risk quickly.

Quantifying the hemorrhage amount and the extent of the injury can C.-T. Cheng et al. Biomedical Journal 48 (2025) 100743 5 provide insights for the clinician regarding the severity of an injured patient’s condition and potential blood loss. Furthermore, these quantifications are correlated with clinical outcomes and decisions. Dreizin et al. have published a series of works in this field. They utilized the Recurrent Saliency Transformation Network for hemorrhage quantification in pelvic fracture to automatically quantify the hematoma [84] and further predict the need for massive transfusion, angioembolization, or pelvic packing, achieving an AUC of 0.83 [85]. When a multiscale attentional network was used to predict composite outcomes, such as hemostatic intervention, transfusion, and in-hospital mortality, it achieved an AUC of 0.86 and a DSC of 0.61 for the hemoperitoneum. They used an ensembled nn-Unet to predict composite outcomes for hemothorax, achieving an AUC of 0.74 and a mean DSC of 0.75 [86,87]. Additionally, a number of teams have worked on quantifying pulmonary contusions and predicting their outcomes. Choi et al. determined the proportion of the contused area in patients with rib fractures using a pretrained lung segmentation U-net model. They discovered the severity linked to extended hospital stays and mechanical ventilation [88]. In order to automate the assessment of the lung contusion index and subsequently forecast the progression of patients to acute respiratory distress syndrome, Sarkar et al. trained a nnUnet on manually labeled pulmonary contusions, attaining an AUC of 0.7 [89].

Since 2017, the RSNA has held an annual AI competition, with the 2023 edition concentrating on abdominal trauma detection [90]. Over 4000 CT scans, including those for a variety of abdominal injuries, were performed during this iteration. Annotations for kidney, liver, spleen, colon, and extravasation injuries are included in the dataset, which was gathered from 23 locations in 14 nations. Notably, extravasation and intestinal damage were given unique image-level designations. It is predicted that the publication of this dataset would spur the creation of high-performance algorithms.

Extremity fractures are the most common condition in trauma patients but are less emergent except for femoral shaft fractures, open fractures, and mangled extremities that require reperfusion procedures. Nevertheless, misdiagnosis of fractures can bring consequences such as malunion, nonunion, avascular necrosis, secondary injuries, and potential lawsuits for medical providers. The vast majority of fractures can be diagnosed initially using plain radiographs of each body part. Some minor or occult fractures can only be visible in CT or MRI under clinical suspicion. Among the limb fractures, wrist fracture is the most studied [91]. Some researchers tried to develop multiregion fracture detection algorithms in plain X-ray [48] and CT [92].

Challenges and limitations

The development of DL models for trauma imaging applications is hampered by a number of issues. First, patient privacy issues limit the acquisition of medical imaging datasets, so limiting the amount of data available to researchers, which serves as the foundation for the development of strong deep learning algorithms. Second, correct medical image labels are costly and dependent on specialized medical professionals. Instead of being tuned for algorithm training, the metadata of images kept in hospital information systems is usually tailored for clinical use. In order to obtain high-quality annotations, researchers are frequently forced to re-label the photos. Last but not least, there is a clear class disparity in disorders as, particularly for rare diseases, the number of normal cases greatly exceeds the number of anomalies in medical practice.

It is difficult to gather high-quality trauma picture databases. In trauma accidents, patient privacy and data security are vital, and a stringent identification procedure is necessary to stop information from leaking. When deciding whether to provide picture files and labels, medical institutions may also be concerned about required legal and ethical restrictions such as the Health Insurance Portability and Accountability Act (HIPAA). Data standardization is further complicated by the fact that imaging procedures vary throughout institutes and the epidemiology of the trauma population varies greatly across areas [93].

Since clinical labels normally only contain radiology reports and Digital Imaging and Communications in Medicine (DICOM) headers, reannotating gathered datasets is frequently required. Although some researchers examine radiologist reports using natural language processing (NLP) technologies, this method can introduce noise into the dataset and produce errors [94]. Report parsing typically only produces exam-level classification rather than precise location information, which is especially restrictive for image series such as multiphase CT scans. For example, the exam-level label would still show an abnormality even though the majority of the slices in a whole-body CT scan of a patient with a slight splenic injury would appear normal. Each image must be manually annotated, which is time-consuming and requires medical knowledge. Furthermore, segmenting the damage location presents a distinct difficulty, particularly for organ injuries. The wounded portion of an organ is frequently irregularly shaped, with poorly defined borders, making the contouring work more difficult than in tumor segmentation, where the aim is more defined. Some scholars have tried techniques like point annotation [47] and creating pseudo labels [95] to solve these annotation concerns, but a broadly applicable solution has not yet been found.

To make model training and evaluation easier, the majority of deep learning models are usually built using balanced datasets, which have an almost equal proportion of positive and negative cases. Conversely, even within a targeted population, clinical circumstances frequently displayed a notable class imbalance [96]. Particularly in certain screening modalities, exams with particular positive results are rather uncommon. As a result, even a classification model that achieves 95% accuracy in a balanced dataset may still generate a significant number of false positive cases when used in practice, which can wear doctors out if the specificity is still subpar.

Local dataset-based models frequently overfit to the training set, which restricts their capacity to generalize to pictures from other sources. Although the DICOM format ostensibly standardizes medical images of the same type, differences in demographic distribution, equipment manufacturers, acquisition techniques, operators, and institution-specific artifacts might impair model performance. By employing produced images or different augmentations, researchers have tried to increase the robustness of their models to new image sources. However, the best way to address this problem is to increase the scale of the dataset to incorporate a variety of sources [20].

Although the U.S. FDA has approved a number of DL-based emergency solutions for clinical use, not all of them have strong, peer-reviewed evidence [97]. For commercially available AI tools, numerous multi-reader, multi-case studies including clinical benefit analysis are currently underway. Pneumothorax in CXR, extremity/junctional zone fracture identification in plain X-rays, detection systems for brain hemorrhage, cervical spine fractures, compression fractures, and rib fractures in CT scans are some examples of these tools. According to a poll, over 50% of members of the American Society of Emergency Radiology employ AI techniques in their work [1]. Although some products have been distributed regionally, regulatory restrictions in each nation and differences in medical practice continue to hinder worldwide dissemination. Furthermore, there are substantial obstacles in moving from the lab to real-world implementation due to the demands for processing power and software engineering. When working with medical imaging, data scientists frequently prioritize optimizing the model's performance above considering the necessary computational resources. However, creating a computer-assisted diagnosis product that is sold commercially is far more difficult and typically calls for a team with a variety of skill sets. In clinical environments, software engineers must give top priority to cost-effectiveness, workflow integration, user-friendliness, computing efficiency, and data protection.

Future prospects and trends

The road to AI is still bright, despite the obstacles that lie ahead. These challenges in creating DL models for trauma imaging may be overcome in a number of future directions. One method that enables several cooperative teams to train the same global model across various servers without exchanging local data is federated learning [93]. This method's benefit is that it can allay worries about data security and privacy while enabling the combining of various datasets for reliable model training. The institution's publicly available datasets may also encourage the computer science community to concentrate on a particular subject and optimize its benefits. In our experience, the majority of scientific breakthroughs are followed by the publication of extensive data on a particular subject.

Furthermore, in order to gain physicians' trust when incorporating AI tools into clinical workflow, DL models must be explainable. The interpretability of AI choices is improved by the development of visualization tools [98]. Certain classification systems are unable to accurately locate the lesion; instead, they can simply provide the prediction probability or outcome. Surprisingly, Cheng et al. discovered that Grad-CAM could precisely locate the lesion site using heatmaps when they used it to the hip fracture detection model [42]. But without any real anatomical justification, the heatmap can simply show the region that the algorithm uses to identify the class. When the dataset is tiny or the difference between classes is less noticeable, CAM-like algorithms frequently fail, even though they are useful in some domains as a weakly supervised approach.

Integrating different data types is made possible by recent developments in multimodal DL model development [99]. It may be easier to comprehend how radiologists' reports and images correlate if language and image models are combined. It will also be feasible to include other clinical data, including demographics, test results, physical examinations, and other modalities. Using pictures to predict patient outcomes is another possible trend. The degree of damage to anatomical structures is reflected in the imaging itself. Healthcare professionals can make better decisions about treatment plans and resource allocation by forecasting probable bleeding quantities and tissue damage, which is consistent with the contemporary idea of precision medicine [100]. By making trauma diagnosis easier, the use of DL as a computer-aided diagnosis system in clinical practice has the potential to alter management paradigms. Finding every lesion is the first step in promptly managing trauma patients, which is essential in a chaotic trauma scene. When specialized resources are limited, AI systems can help doctors quickly detect injuries that need management, increasing patient outcomes and the standard of healthcare.

Conclusion

Significant progress has been made in the use of DL in trauma imaging in recent years. Although certain sectors are still in the early stages of development, researchers have produced encouraging outcomes in a number of domains. However, there are still many obstacles to overcome, such as the need for labeling, privacy issues, and data collection. The combined effort in model development will eventually allow AI-powered trauma imaging solutions to be incorporated into our clinical practice, enabling the quick and precise detection of potentially fatal injuries. The adoption of this new technology by healthcare personnel will improve diagnostics' accuracy, effectiveness, and patient-centeredness.

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