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Automated Midline Shift Detection and Quantification in Traumatic Brain Injury: A Comprehensive Review

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Abstract

Traumatic brain injury (TBI) often results in midline shift (MLS) that is a critical indicator of the severity and prognosis of head injuries. Automated analysis of MLS from head computed tomography (CT) scans using artificial intelligence (AI) techniques has gained much attention in the past decade and has shown promise in improving diagnostic efficiency and accuracy. This review aims to summarize the current state of research on AI-based approaches for MLS analysis in TBI cases, identify the methodologies employed, evaluate the performance of the algorithms, and draw conclusions regarding their potential clinical applicability. A comprehensive literature search was conducted, identifying 15 distinctive publications. The identified articles were analyzed for their focus on MLS detection and quantification using AI techniques, including their choice of AI algorithms, dataset characteristics, and methodology. The reviewed articles covered various aspects related to MLS detection and quantification, employing deep neural networks trained on two-dimensional or three-dimensional CT imaging datasets. The dataset sizes ranged from 11 patients' CT scans to 25,000 CT images. The performance of the AI algorithms exhibited variations in accuracy, sensitivity, and specificity, with sensitivity ranging from 70 to 100%, and specificity ranging from 73 to 97.4%. AI-based approaches utilizing deep neural networks have demonstrated potential in the automated detection and quantification of MLS in TBI cases. However, different researchers have used different techniques; hence, critical comparison is difficult. Further research and standardization of evaluation protocols are needed to establish the reliability and generalizability of these AI algorithms for MLS detection and quantification in clinical practice. The findings highlight the importance of AI techniques in improving MLS diagnosis and guiding clinical decision-making in TBI management.

Keywords
- midline shift
- deep learning
- traumatic brain injury
- automated detection
- computed tomography
- artificial intelligence

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Introduction

Traumatic brain injury (TBI) is a complicated and often baffling episode characterized by alterations in consciousness with evidence of brain pathology caused by external forces. Described as "the silent epidemic," TBI is projected to surpass many other diseases as the leading cause of death and disability by 2020, as reported by the World Health Organization.[1]

Depending on the type and magnitude of the external forces causing the initial insult, a diverse range of radiological abnormalities or lesions can be observed in TBI patients.[2] The immediate effects include hemorrhage and fractures, whereas the secondary effects are the midline shift (MLS) and changes in intracranial pressure (ICP). MLS serves as a critical measurement for assessing brain symmetry changes and is an essential indicator of pathological severity.[3] Remarkably, even a small hematoma can lead to focal neurological deficits, while mortality resulting from a large hematoma directly correlates with brain stem compression that is evident through MLS measurement.[4] A shift in the midline of more than 5 mm on the initial brain computed tomography (CT) images is considered significant and predicts poor neurological outcomes.[4,5]

Head CT scans are widely accessible, rapid, and noninvasive, mode for the initial assessment and diagnosis of TBI in emergency settings.[6] During the acute phase following TBI, head CT is commonly employed to identify critical brain pathologies and quantify the extent of the injury. The volume of lesions caused due to TBI and associated secondary features such as greater MLS and ICP are important factors for the clinical management of patients.[1]

The degree of MLS following TBI is widely recognized as a significant indicator of severe injury. Several reports have established a strong association between a substantial amount of MLS observed on CT scans and unfavorable outcomes including disability or mortality in TBI cases.[5,7] MLS represents the extent of brain displacement resulting from the injury itself.[3,7] For instance, analysis of data from the National Traumatic Coma Data Bank revealed that among 18 patients who experienced initial speech ability but later deteriorated, 7 had an MLS exceeding 15 mm.[3] The measurement of MLS serves as a valuable tool in assessing the severity of TBI and predicting the related clinical outcomes.[7] An MLS of less than 5 mm is considered less serious, while an MLS exceeding 5 mm necessitates neurological attention and potential surgical intervention.[8] Severe brain trauma leads to brain swelling, causing imbalanced pressures between the left and right hemispheres. This pressure imbalance further deforms the ideal midline (IML) into a curve known as the deformed midline (DML).[3,7]

The brain midline is not an anatomical feature but is represented by a curve connecting the attachment centers of the falx. It is an imaginary straight line that divides the brain into two equal hemispheres referred to as the IML.[3] The IML can be defined as a hypothetical line passing through the pineal gland, septum pellucidum (SP), and cerebral falx. The straightforward definition of MLS can be a deviation from the actual/IML of the brain.[8]

Various authors often describe MLS in terms of the displacement of the SP, relative to the IML observed on CT images.[9,10] Deviation of the midline structure, whether it be the pineal gland, third ventricle, or SP, from the IML is also labeled as a MLS. When midline structures undergo a shift, it is presumed to represent a mass lesion on the side from which the midline is displaced, as symmetry plays a critical role in radiologic brain evaluation.[7] MLS is defined as the displacement of the brain from its assumed center line, and it can be quantified by measuring the perpendicular distance between the IML and the shifted SP, and a common practice is to measure the maximum distance from the midline formed by the anterior falx and posterior falx to the SP at the axial level of the foramen of Monro.[8,9,11]

The Brain Trauma Foundation initially proposed a manual measurement method for MLS.[12] It involved measuring the intracranial width at the level of the foramen Monro and then determining the distance from the inner skull to the SP.[8] Another approach suggested measuring the distance from a line connecting the most anterior and posterior visible points on the falx to the farthest point on the SP.[13] However, manual drawing of MLS can be time-consuming and prone to interrater variability, reducing its reliability. Consequently, several computer-aided or automated methods have been developed to provide an objective and robust MLS measurement approach.[8]

Given its diagnostic significance, the development of automated tools for MLS detection and computation using image processing techniques is of paramount importance. An efficient algorithm to compute MLS is a crucial component of computer-aided neurology diagnosis systems. Implementing an automated detection system can promptly flag cases requiring urgent review, facilitating timely care provided by clinicians.[8]

Although the automated system is not intended to surpass the expertise of specialists such as neurosurgeons, neurologists, or neuroradiologists, it can save their time and offer valuable objective information, especially in emergency settings. Careful screening by the automated system might also provide insights for further management, enabling first-line physicians to reconsider injury severity and prioritize accordingly. Therefore, while an expert's diagnosis remains irreplaceable, the use of automated standardized image-based systems is recommended due to their objectivity and generally faster results.[8]

In our review paper, we have also addressed the limitations of current AI methods and highlighted future research directions for enhancing automated CT identification and quantification of TBI-related lesions. Recent studies in CT image recognition have heavily relied on deep neural network frameworks, particularly those employing convolutional neural network (CNN) architecture.[14] The aim is achieved by studying the available literature linking automation, CT scans, and TBI.

Aims and Objectives

The aim of this review article is to provide a comprehensive overview of automated MLS detection and quantification studies conducted in TBI cases. Additionally, this review aims to evaluate the existing manual and automated methods for MLS measurement and explore the benefits and limitations of automated MLS detection systems in facilitating timely care. Furthermore, it aims to identify gaps in current research and propose future directions for enhancing the accuracy and reliability of automated detection and quantification of MLS.

Materials and Methods

A systematic search was conducted to identify relevant studies focusing on automated MLS detection and quantification in patients with TBI. The electronic databases of Google Scholar and PubMed were extensively searched to retrieve articles related to machine learning or deep learning studies in medical image analysis, MLS, and TBI. A combination of Medical Subject Headings terms, specific keywords, and phrases associated with MLS pathology in TBI was used to optimize the search results.

The inclusion criteria for selecting relevant articles were as follows: studies related to automated analysis of MLS in humans caused by TBI using head CT scans or images, studies related to automated detection, measurement, and quantification of MLS in TBI cases, articles from peer-reviewed journals, systematic reviews, and webpages related to artificial intelligence/machine learning, and articles published between 2003 and 2023. Only articles written in the English language were included.

Exclusion criteria were applied to exclude studies conducted on animal subjects, studies focusing on treatment strategies, prognosis, and prevention, MLS caused by conditions other than TBI (such as tumors or strokes), studies utilizing imaging techniques other than CT scans (e.g., sonography or magnetic resonance imaging), biochemical, statistical, or biological markers research related to MLS, scientific abstracts, conference proceedings, letters to the editors, articles without full text, and articles published before 2003.

The search process involved using a combination of keywords, including "traumatic brain injury," "automated midline shift detection," "automated midline shift measurement," "midline," "MLS estimation," "computer-aided diagnosis," "intracranial pressure levels," "brain midline shift," "automatic detection and classification," "CT images," and "quantification." The search was conducted within a specific timeframe, and the keywords used were MLS and TBI.

The identified studies on the development and validation of deep learning/machine learning-based analysis of MLS using head CT scans were thoroughly reviewed and analyzed for their relevance to the topic of interest.

Results

Approximately 60 distinctive publications were reviewed to identify studies focusing on automated detection and quantification of MLS from head CT scans in TBI cases using artificial intelligence (AI) techniques. After applying the inclusion criteria, 15 articles were deemed eligible for inclusion in this review.

The identified articles covered various components related to the identification and quantification of MLS from head CT scans, including detection, localization at the slice, pixel, and voxel levels, and measurement of MLS. The majority of the AI algorithms employed in these studies were based on deep neural networks and trained using two-dimensional (2D) or three-dimensional (3D) CT imaging datasets. The dataset sizes varied among the studies, ranging from 11 patients' CT scans to 25,000 CT images.

The performance of the AI algorithms, as reported in the reviewed articles, showed variations in accuracy, sensitivity, and specificity (►**Table 1**). While specific numerical values were not provided for all studies, the range of accuracy achieved was notable, with sensitivity values ranging from 84.6 to 100% and specificity values ranging from 73 to 97.4%. The techniques used by the reviewed work are the landmark-based approach and the symmetry-based approach, but all the works cannot be rigidly classified into these two buckets. Hence, it is important to note that direct comparisons between different techniques may not be feasible.

Discussion

In recent years, there has been a growing interest in utilizing AI techniques to automate radiological procedures in TBI cases. However, a comprehensive investigation and synthesis of these AI-based studies focusing on the identification and quantification of MLS in TBI cases are currently lacking. Building upon our previous work on intracranial hemorrhage (ICH) detection in TBI, which outlined future research directions,[15] this review aims to address this gap by specifically examining the detection and quantification of MLS in TBI cases.[14]

The field of automatic MLS measurement has witnessed significant advancements, with several approaches being proposed to quantify MLS from head CT scans. These automatic methods leverage the symmetry of the brain or utilize specific anatomical landmarks, such as the falx cerebri, frontal horns of the lateral ventricles, and the third ventricle. By exploring and comparing these approaches, we aim to provide valuable insights into their effectiveness, limitations, and potential applications in clinical practice.[16] By conducting a systematic review and analysis of the existing literature, we aim to consolidate the current knowledge on automated MLS detection and quantification in TBI cases.

The Symmetry-Based Approach

This approach is based on the concept of symmetry around the brain's midline. It does not require the recognition of

Table 1 List of articles

Sl. no.	Name	Author	Year	Approach	Data	Result
1	Automatic recognition of midline shift on brain CT images	Liao et al[10]	January 2010	Symmetry based	81	85% in 65 cases
2	Automated midline shift and intracranial pressure estimation based on brain CT images	Chen et al[16]	April 2013	Symmetry based	371 slices from 17 TBI cases	70% sensitivity 65% and specificity 73%
3	From hemorrhage to midline shift: a new method of tracing the deformed midline in traumatic brain injury CT images	Liu et al[21]	2009	Symmetry based	11	NA
4	Computer-aided assessment of head computed tomography (CT) studies in patients with suspected traumatic brain injury	Yuh et al[6]	2008	Symmetry based	250 CT scans	Sensitivity of 92% and specificity of 85%. PPV of 70%
5	Automated assessment of midline shift in head injury patients	Xiao et al[18]	June 2010	Landmark based	96 CT scans	Sensitivity 94%, specificity 100%
6	Automatic measurement of midline shift on deformed brains using multiresolution binary level set method and Hough transform	Xiao et al[17]	June 2011	Landmark based	80 CT scans	NA
7	Automatic detection and quantification of brain midline shift using anatomical marker model	Liu et al[3]	November 2013	Landmark based	7,040 CT images	Standard deviation 0.088, mean area ratio 0.076
8	Deep learning algorithms for detection of critical findings in head CT scans: a retrospective study	Chilamkurthy et al[19]	October 2018	Landmark based	Qure25k, CQ500	Sensitivity 0.89
9	Brain midline shift detection and quantification by a cascaded deep network pipeline on noncontrast computed tomography scans	Nguyen et al[11]	2021	Landmark based	25,037	Accuracy 0.89
10	A simple, fast and fully automated approach for midline shift measurement on brain computed tomography	Wang et al[4]	March 2017	Landmark based	43 CT scans	Accuracy 90.24%
11	Automatic quantification of computed tomography features in acute traumatic brain injury	Jain et al[1]	June 2019	Landmark based	38	Mean absolute difference 0.86mm
12	A robust, fully automatic detection method and calculation technique of midline shift in intracranial hemorrhage and its clinical application	Yan et al[8]	March 2022	Landmark based	300 CT scans	Sensitivity, specificity: MLS at 2 mm (91.7%, 80%) and 5 mm (87.5%, 96.7%), MLS $<$ 10 mm (85.7%, 97.7%).

(*Continued*)

Table 1 (*Continued*)

Sl. no.	Name	Author	Year	Approach	Data	Result
13	Automatic midline shift detection in traumatic brain injury	Hooshmand et al[7]	2018	Landmark based	170 CT scans	NA
14	The delineation of largely deformed brain midline using regression-based line detection network	Wei et al[20]	Accepted article	Landmark based	CQ500 (128 CT scans) + 61 (Validation dataset)	NA

Abbreviations: CT, computed tomography; MLS, midline shift; NA, not available; PPV, positive predictive value; TBI, traumatic brain injury.

specific anatomical landmarks. Instead, it seeks to identify a curve that connects all displaced and deformed structures, known as the "deformed midline" (DML).[9,10] We will delve into studies that have adopted the symmetry-based approach to measuring MLS in TBI cases.

Liao et al proposed a novel approach known as the "skull axis" method for measuring MLS on CT slices at the level of the foramen of Monro. Their method approximated the IML by using the axis of the skull, represented by a line connecting the attachments of the falx. They developed an algorithm for automated MLS measurement on normal and TBI CT slices. The algorithm was tested on 81 clinical cases, and they achieved an accuracy of 95% in measuring MLS magnitudes among the 65 TBI cases (80%). However, their method showed moderate accuracy in detecting MLS and had lower accuracy in detecting large MLSs (>5 mm) with spontaneous ICH. Their approach also had certain limitations, such as the need for manual slice selection and limited performance in severe TBI cases.[10]

Chen et al incorporated both symmetry-based methods and shape-matching techniques for MLS identification, aiming to correlate MLS with the level of ICP. The authors employed a hierarchical search based on skull symmetry, falx, and interhemispheric sulcus to identify the IML. They tested their method on a dataset of 391 slices from 17 TBI patients, evaluating the detection of the IML, DML, MLS measurement, and ICP estimation. The results showed that errors between the IML were approximately 1 mm. For the DML, over 80% had a difference of less than 2.25 mm, provided that the ventricular segmentation quality was relatively good. However, the method encountered difficulties when the ventricles could not be identified due to significant brain deformation. The accuracy achieved in their study was approximately 70%, with a sensitivity of about 65% and a specificity of about 73%.[16]

Liu et al developed a heuristic model called hemorrhage-MLS (H-MLS) to explore the relationship between ICH and MLS. The model was developed using 11 CT images and 423 midline points, employing 10-fold cross-validation. The H-MLS model utilized linear regression to identify hemorrhage and the associated MLS. Although specific algorithm details were not provided, the model was implemented using MATLAB. The authors mentioned that the technique is time efficient but did not provide clear results. It should be noted that this method may not be effective in cases of chronic hemorrhage due to the difficulty in segmenting low-intensity chronic hematoma.[3]

Based on our observations, few researchers faced challenges to estimate MLS when it was larger. And others are focused on addressing this challenge. Yuh et al focused on detecting MLS larger than 5 mm. Their computer-based approach involved developing a suite of algorithms within MATLAB. The method relied on assessing the symmetry of cerebrospinal fluid pixels within the lateral ventricles in relation to the IML determined by the skull's symmetry axis. The software was validated using a sample of over 200 patients suspected of acute TBI. The automated detection of either of the radiological sign of acute TBI demonstrated a high sensitivity of 98%. Although quantitative MLS measurement results were not reported, the method achieved a sensitivity of 92% and a specificity of 85% for detecting MLS larger than 5 mm. However, due to the limited number of patients with such findings and additional false-positive results, the positive prediction rate of their MLS detection method was only 70%.[6]

Mohsen utilized ventricular geometric patterns and anatomical information to identify the IML. The proposed method, implemented in "MATLAB 2016b," estimated the MLS as the distance between two lines. The dataset comprised approximately 170 sets of CT scans from TBI patients, and a symmetry-based approach was adopted. The estimation of the actual midline involved a simple thresholding approach to segment ventricles.[7]

The Landmark-Based Approach

In landmark-based algorithms, the focus is on recognizing specific structures, typically frontal horns of the lateral ventricles, SP, third ventricle, etc. These structures serve as anatomical markers for MLS measurement. Among the identified landmarks, the most suitable ones are chosen to construct the DML, which is then compared to the IML for quantifying MLS. This approach allows for targeted analysis and measurement of MLSs based on anatomical markers within the ventricular regions.[6,9]

Xiao et al proposed a procedure for measuring MLS by recognizing the SP. Their system was tested on images from 96 patients. The algorithm accurately measured MLS up to 30 mm and showed a mean difference of 0.23 ± 0.52 mm compared to manual measurements in 78 cases. The algorithm faced difficulties in recognizing frontal horns in images of patients with large ICHs. Nonetheless, the method demonstrated robustness and applicability in emergency and routine settings. Xiao's approach achieved a sensitivity of 94%, specificity of 100%, and positive predictive value of 100% for MLS more than 5 mm. While the algorithm performed well with small MLS, accurately measuring large MLS with significant hematoma posed a challenge.[17,18]

Liu et al utilized a Gaussian mixture clustering process to detect cerebrospinal fluid regions and landmark pixels within them. A Gaussian mixture model was trained on data from the middle slice of 200 patients. The method was tested on an experimental dataset with 565 patients. The system selected the middle slice, identified anatomical markers, and calculated the MLS, providing area ratio and maximum distance outputs. It automatically detected and quantified MLS, generating an XML document for retrieval purposes. The method achieved a maximum distance error of 4.7 ± 5.1 mm, and more than 100 patients had an MLS larger than 5 mm.[3]

Chilamkurthy et al conducted MLS detection on two datasets: Qure25k, consisting of 25,000 images with an area under the curve (AUC) of 0.93, and CQ500, comprising 500 images with an AUC of 0.97. Their method achieved an average sensitivity of 0.89 for MLS detection larger than 5 mm. On the other hand, Nguyen et al proposed a landmark-based system with two modules for MLS detection and quantification. They collected a dataset of 25,037 CT volumes from multiple centers, achieving a total accuracy of 0.89. When comparing the performance of Nguyens et al's method to Chilamkurthy et al's work, it was observed that Nguyens et al achieved higher detection performance in terms of AUC for the equivalent-size dataset of 25k images, but lower AUC was obtained with the smaller CQ500 dataset.[11,19]

In 2017, Wang et al developed a method for automatically measuring MLS with an average processing time of around 10 seconds. This method involved plotting a weighted midline (WML) based on pixel intensities, with higher weights assigned to darker portions. The distance between the WML and the IML near the foramen of Monro was then measured as the MLS. Although the algorithm details were not mentioned, their automated system achieved an overall accuracy of 90.24% when the CT images were calibrated automatically. The system performed even better when the calibrations of head rotation were done manually, with an accuracy of 92.68%. Additionally, they reported an accuracy of 0.90 for MLS detection larger than 5 mm in a study involving 43 subjects.[4]

In a more recent study, Jain et al introduced Icobrain, a segmentation and MLS detection method based on U-Net. Their approach involved using a 2D U-Net-based method for image segmentation and subsequently calculating the MLS. The study included a dataset of 38 images, and the analysis showed a median absolute difference in MLS of 0.86 mm, with an intraclass correlation coefficient (ICC) of 0.93. The images were collected by icometrix, and MLS data were obtained from structured radiological reports indicating the MLS status ($<$5 mm or $>$5 mm). Measurements were performed at various levels, ranging from the foramen of Monro to the roof of the lateral ventricles, where MLS could potentially be observed. The classification accuracy achieved at the conventional threshold of 5 mm was 0.89.[1]

Yan et al's study revealed significant findings regarding the automatic detection of MLS. The comparison between the automatic detection method and manual drawing showed a mean absolute error of approximately 0.93 mm and a high ICC of 0.9899, indicating strong agreement. Additionally, the data demonstrated good sensitivity ranging from 84.6 to 91.7% and specificity ranging from 80 to 97.4% in detecting MLSs of 2 and 5 mm greater than 10 mm. The utilization of key point R-CNN allowed for accurate identification of the falx cerebri and the SP, without the need to identify intricate brain structures. The study encompassed 7,269 CT slices obtained from 300 patients, and the developed fully automatic detection method exhibited a strong correlation with manual drawing, demonstrating its effectiveness in detecting both small MLSs ($<$2 mm) and large MLSs ($>$10 mm).[8]

In a separate study conducted by Wei et al, a CNN-based model was developed to measure MLS in TBI patients. The model achieved average distance errors of 1.1 ± 70.72 mm on the CQ500 dataset and 4.15 ± 3.97 mm on the internal dataset of 61 Head CT scans which was the validation dataset. The aim was to estimate the extent of MLS using the proposed model, demonstrating its effectiveness in quantifying MLS.[20]

Overall, the results indicate that AI-based approaches, primarily utilizing deep neural networks, have promising results in the automated detection and quantification of MLS in TBI cases. The findings highlight the potential of AI techniques in improving the efficiency and accuracy of MLS identification and quantification. However, due to the variations in methodologies and limited direct comparisons between different studies, it is crucial to carefully evaluate each approach's individual merits and limitations.

Conclusion

In conclusion, the measurement and estimation of MLS in patients with TBI using CT scans have emerged as a valuable tool in clinical practice. MLS estimation has proven to be a crucial feature that aids clinicians in making informed decisions regarding the management and treatment of TBI patients.

Variations in study designs, small sample sizes, and lack of standardized MLS measurement techniques among studies pose challenges in directly comparing results and drawing definitive conclusions. Additionally, the rapid advancements in MLS detection methods and the potential exclusion of recent studies due to the review article's knowledge cutoff may impact the comprehensive understanding of this field.

Future research efforts should focus on standardizing MLS measurement techniques, incorporating larger and more diverse study populations, and providing detailed algorithm descriptions to address these limitations. These advancements will enhance the accuracy and applicability of MLS estimation in clinical settings, ultimately facilitating better patient management and outcomes for individuals with TBI.

Conflict of Interest
None declared.

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