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Artificial Intelligence Techniques for Effective Detection of TBI From CT Scans- Novel Perspective in the Clinical Care of TBI Patients: A Systematic Review

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Abstract: Aim: To effectively detect traumatic brain injury (TBI) from CT scans and determine their possible effects on clinical care, artificial intelligence (AI) techniques are now being researched. This systematic review intends to examine the present state of that research.
Theoretical Background: The most prevalent cause of mortality and disability worldwide is TBI, also referred to as traumatic brain injury. Traumatic brain injury (TBI) therapeutic care continues to face difficulties due to the requirement for early and accurate identification. The ability of traditional methods of detection, such as CT scans, to provide an accurate diagnosis of traumatic brain injury (TBI), is limited. Artificial intelligence (AI) has been used in recent years to make TBI detection faster and more accurate. According to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, the goal of this systematic review is to find out how AI approaches can be used in the clinic to find TBI patients.
Methods/ Approaches: A comprehensive search was conducted across major scientific databases, resulting in the identification of 55 relevant studies published up to the present date. These studies incorporated various AI methodologies, including deep learning, machine learning, and computer vision algorithms, for TBI detection using CT scans. Quality assessment and data extraction were performed systematically to ensure rigour and consistency.
Conclusion: In conclusion, this systematic review underlines the transformative impact of AI techniques in TBI detection from CT scans, presenting a novel perspective in the clinical care of TBI patients. AI holds great promise in optimizing TBI diagnosis, streamlining clinical workflows, and enhancing patient outcomes. As AI technologies advance, collaborative efforts between researchers, clinicians, and policymakers are essential to establish guidelines, address challenges, and ensure the ethical and responsible integration of AI in TBI patient care.

Keywords: *Traumatic brain injury (TBI), CT scans, AI, ML, Deep learning models, Segmentation*

1. Introduction

Traumatic brain injury, also known as TBI, is a dangerous condition that changes how the brain functions. It results from a brain damage. In the modern world, it is the leading cause of death and disability among teenagers and young adults [2, 42]. Numerous events, such as a car accident, a fall, an injury experienced while participating in sports, or an act of violence, can result in a traumatic brain injury (TBI) [16][18]. Since there are only a few imaging modalities that may be utilized for diagnosis and no trustworthy biomarkers that can determine the amount of damage, Traumatic brain injury (TBI) can be hard to figure out and treat [27].

TBI is a major problem in terms of public health all over the globe, impacting millions of individuals every year. It is a sort of physical trauma to the brain that is induced by an external force, and it is usually caused by things like car accidents, falls, injuries sustained in sports, and acts of physical aggression. The ramifications of a traumatic brain injury are far-reaching and may have lasting repercussions on a person's physical and mental capabilities [50]. Medical professionals face a severe challenge when it comes to the identification and treatment of traumatic brain damage, and more effective diagnostic methods are urgently needed [45].

Youth TBI is one of the primary causes of demise and impairment. More people than one are affected by it 400 people in Europe. As a result, it significantly affects society in terms of both people and resources. If the first aggression results in primary lesions, which develop immediately and cannot be prevented, it may also generate delayed lesions, which are referred to as secondary injuries, and they have a significant impact on the fate of the neurological condition [30][39]. The primary and secondary injuries are shown in Figure 1

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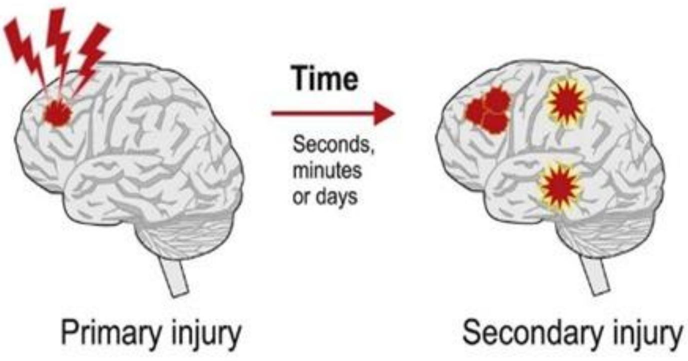

Fig 1: Primary and secondary injury of TBI [30]

As a result, the objective of the intensive care management of patients with TBI is to reduce the risk of subsequent brain injuries by using treatments that are tailored to the degree of severity of the patient's conditions [26].

The clinical evaluation and first brain imaging are what are used to determine how severe a traumatic brain injury is. Clinical examination is not reliable in the early stages of traumatic brain injury; rather, it is predicated on pupillary responsiveness as well as the Glasgow Coma Scores (GCS), which categorises the severity of traumatic brain injury into mild, moderate, or severe phases [35]. As a consequence of this, the GCS categories encompass a broad pattern of traumatic brain injury and are not able to discern between particular developments such as focal lesions and diffuse damage. Figure 2 depicts the categorization of focal and diffuse injury. A brain imaging scan, more specifically a computed tomography (CT) scan, is an alternative diagnostic technique that may help TBI patients be more accurately classified. Imaging ratings have been constructed by researchers to define and quantify brain lesions, and these scores are based on the results from the radiological readings [9]. The Marshall categorization, the Rotterdam scoring, the Stockholm scoring system, and the Helsinki score are some of the scores that have been produced [36]. There is a correlation between each score and the neurological result, which is measured by the Glasgow Outcome Scale (GOS).

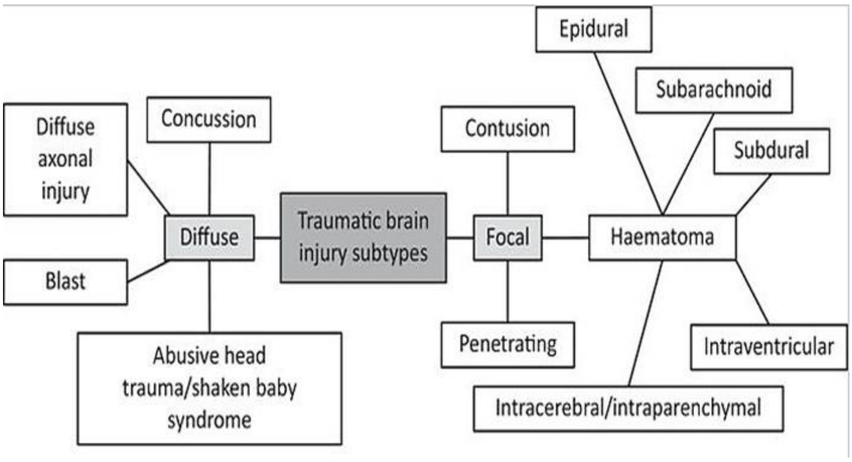

Fig 3: Categorization of TBI into focal and diffuse injury [9]

However, the application of these CT scan results does come with a few downsides to consider. One problem is that their replies are dichotomized, meaning they can only be yes or no. This may cause an underestimation of the worldwide impact that minor intracerebral lesions have. When using these ratings, it is important to keep in mind that there is inter-observer variability, even though they are very easy to calculate [40]. Last but not least, classifying each individual within a CT scan rating requires a significant investment of human resources. This may be the reason why clinical practices do not make use of these scores. In this context, there has been an uptick in interest among doctors in the creation of computer-based methods for determining the kind and amount of traumatic brain injuries based on CT images [33].

The computed tomography (CT) scan is a common imaging technique used to diagnose traumatic brain injury (TBI). It provides a complete three-dimensional view of the brain and is especially useful for identifying structural damage brought on by traumatic brain injury (TBI) [17]. After that, the pictures from the CT scan are analysed to determine the extent of the damage and to locate any intracranial abnormalities that may be connected with it. However, the interpretation of CT scans is a procedure that requires a lot of manual effort, and a significant amount of time, and may result in accuracy [35]. In addition, the interpretation of CT scans might differ from one radiologist to the next, which can result in findings that are not consistent.

Computed tomography (CT) scans are now the gold standard for diagnosing traumatic brain injury (TBI). CT scans are painless and give in-depth information on the anatomy and function of the brain without the need for any intrusive procedures [21]. They are used in the process of diagnosing the existence of aberrant intracranial lesions, such as oedema, bleeding, contusions, or fractures of the skull [51].

The overarching notion of artificial intelligence (AI) continues to be muddled as a result of the philosophical connotations associated with the term intelligence. Notwithstanding, an area of artificial intelligence known as "machine learning" (ML) refers to all techniques that permit unprogrammed machine learning from data [15]. The term "AI" can be used to allude to a branch that concentrates on developing intelligent systems in computer science. You can use both of these meanings simultaneously. The increase in computing power capacity at the outset of the year 2000 and the establishment of big databases have shown how effectively AI algorithms deployed to medical imaging may enhance clinical treatment [43]. This was made possible by the growth in the amount of data that could be stored. The most popular technique for predicting the results of biomedical imaging operations among the three learning approaches that can be employed with [38] Supervised learning is used in machine learning techniques such as reinforcement learning and unsupervised learning. In this method, the algorithms just find the link between the data they are given and the variable they are trying to predict. since both are already known. If one were to simply follow the technique, this developing field of research might be helpful in the statistical study of CT scans and present fresh viewpoints on the care of patients with TBI.

Techniques based on artificial intelligence (AI), which are getting increasing attention as a viable solution to solve the limitations of present approaches for diagnosing traumatic brain injury (TBI), AI technologies such as deep learning may be used to automate the process of processing CT images and the resulting diagnosis of Traumatic brain injury (TBI) diagnosis may be more precise and sensitive. than that provided by conventional diagnostic approaches [37]. Traditional techniques may be unable to identify small changes in the brain, but AI-based systems can. This is something that conventional approaches may overlook. Additionally, artificial intelligence (AI)-based systems may be utilized to identify brain patterns that can be used to determine how severe traumatic brain injury will be. (TBI) as well as the prognosis for someone who has experienced TBI [23]. Finally, AI-based systems may be utilized to automate the process of diagnosing traumatic brain injury (TBI). These systems can manage massive amounts of data in a relatively brief period.

2. Literature Review

The goal of this thorough literature review is to look at the research that has already been done on using AI methods to find TBIs with CT scans. The results of this study will help us learn more about how AI methods for traumatic brain injury diagnosis, in addition to contributing to the identification of possible areas for additional research and improvement.

The use of AI strategies has the potential to completely transform how TBI is identified and treated. In addition to providing information on the degree of the damage and the patient's prognosis, AI-based solutions may provide a diagnosis that is more precise and sensitive to traumatic brain damage than traditional approaches [25]. Additionally, AI-based systems can be taught to automatically detect traumatic brain injury (TBI), manage enormous volumes of data in a very short amount of time, and handle other complex tasks.

Following a TBI event, intracranial injuries may occur, with the greatest death percentage.

Intracranial haemorrhage (ICH) can result in a brain haemorrhage, which is clinically regarded as the most serious case in therapy since, if not treated correctly, it may cause death or total bodily paralysis [53]. One of the most crucial tools for the examination of TBI patients in an emergency is a CT scanner [54]. [55] released a comprehensive review of the literature on IoT-based healthcare applications that leverage the advantages of mobile computing. [52] provided business analytics services and IoT-based cancer care solutions.

3. Significance and Relevance of the Research

Even though computed tomography (CT) is the diagnostic tool that is employed most often, this procedure has several drawbacks. To begin, CT has a restricted capability when it comes to identifying minute or elusive alterations in the brain [22]. Additionally, to correctly interpret the findings of a CT scan, you need highly specialized equipment and employees who have received training. This might cause diagnostic and therapeutic delays. Last but not least, computed tomography (CT) might be too costly in many contexts [15]. AI-based methods have been suggested as a way to deal with the problems that come with figuring out what a CT picture means. AI techniques Computer vision, "deep learning," and other techniques like "machine learning" may be utilized to automatically extract features from CT scans and categorise the extracted data into a variety of distinct categories [6]. It has been demonstrated that AI algorithms are more reliable and accurate than manual interpretation by radiologists when making a traumatic brain injury (TBI) diagnosis. Additionally, techniques from the artificial intelligence field may be used to merge clinical data with CT metrics to achieve greater diagnostic precision [32][48].

4. Research Questions

The review will concentrate on fresh viewpoints in the therapeutic treatment of individuals with traumatic brain injuries as well as the potential of AI techniques to help with traumatic brain injury diagnosis and care. More specifically, the research will answer the questions that are as follows:

1. What are the various aspects that may be retrieved from CT images of people who have had traumatic brain injuries?
2. What are the numerous classifiers that may be utilised on a CT scan, and how are they being used in the literature?

To get a more accurate categorization of traumatic brain injury (TBI) patients, would it be viable to integrate clinical data with CT metrics?

5. Methods

5.1 Selection of primary studies:

Locate pertinent papers for the databases MEDLINE, PubMed, EMBASE, and Web of Science were searched for literature. The phrases "artificial intelligence" and "TBI" were used to search for the information. There was no enforcement of the language ban. The search looked at the years 2017 to 2021, which were the recent years available. Research articles written in English were taken into consideration for the review.

5.2 Eligibility Criteria

We conducted this review based on Prisma guidelines and the detailed inclusion and exclusion criteria used in the article selection are listed in Table 1.

Table 1: Inclusion and Exclusion criteria

Publication Category	Inclusion criteria	Exclusion Criteria
Research design and methodology	Research projects that used methods of artificial intelligence to diagnose traumatic brain injuries using CT images. Studies that focused on the efficacy of the AI approaches for traumatic brain injury identification Research projects that took into account fresh points of view in the treatment of TBI patients	Research projects that focused on the application of AI methods for use other than TBI diagnosis. Research that did not concentrate on providing innovative therapeutic perspectives for the treatment of TBI patients. Studies that did not explicitly utilise CT scans to look for signs of traumatic brain injury Research that did not include any kind of assessment of the various AI approaches.
Language	English	Other languages

5.3 Study Identification and Selection

The investigation lasted from April 2017 until April 2021. The first search brought up 1363 entries, of which 862 were found to be duplicates and were eliminated. To determine which of the remaining 501 records included research that was pertinent to the issue, The records' headings and summaries were examined. After the initial screening, 161 studies were selected to undergo a more in-depth examination. After that, full-text publications were obtained and reviewed to establish whether or not the studies were eligible. 55 papers were selected for inclusion in the systematic review after the second screening. PRISMA flowchart depicting the detailed screening of the collected papers is provided in Figure 3.

5.4 Risk of Bias and Strength of Evidence Assessment

In evaluating, the Newcastle-Ottawa Scale was the studies' overall level of quality (NOS). The NOS is a three-point scale that includes three different components (selection, comparability, and result) and each gets a score between 0 and 2 points. The overall score of each research was determined, and then the studies were arranged in the following categories according to their scores:

a. Low-quality products: 0–4 points
b. average Quality: 5 to 6 points
c. Considerable improvement: 7-9 points

The reliability of the evidence was assessed using the GRADE method. The GRADE system is a five-point scale that rates the quality of evidence as very low, low, moderate, high, or very high, depending on how strong the evidence is. Two different reviewers each gave their own opinion on the reliability of the evidence. Both a narrative style and evidence tables were used to provide a summary of the findings. In the tables of evidence, we included both the features of the studies and an evaluation of the quality of each research.

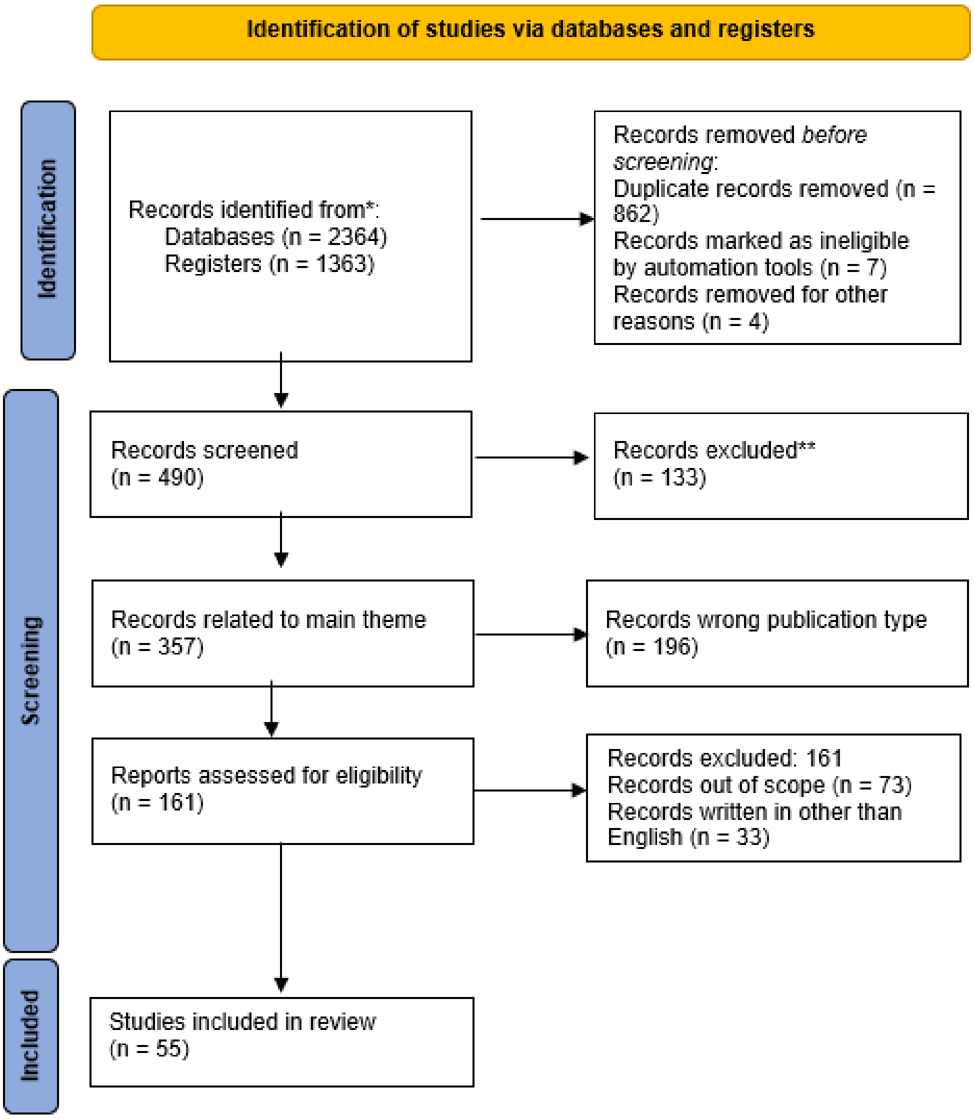

Fig 3: Prisma model for data selection

5.5 Data Extraction

The included studies were analysed, and data were retrieved from them using a standardised manner. Figure 4 displays the distribution of the papers evaluated in this study by year. Data that was retrieved comprised the names of the authors, the year the research was published, the study design, patient characteristics, imaging modality, segmentation method, and assessment of AI approaches. Two different reviewers checked and double-checked the accuracy of the data retrieved from each research.

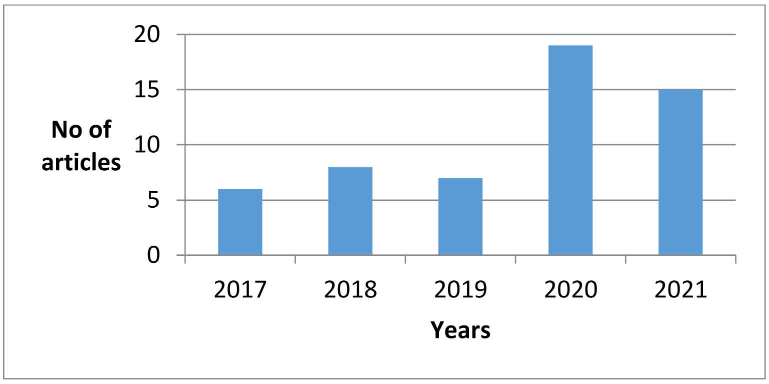

Fig 4: Papers included in the survey by publication years

6. Results

The overall criteria for the systematic review were satisfied by different pieces of research. The research that was included in this review was carried out in a variety of nations, including the United States of America, China, India, and the United Kingdom, and was published between 2017 and 2021. In the trials, researchers used a variety of imaging techniques, including CT scans, MRIs, and PET scans, among others. The 55 papers that were analysed for this systematic review all employed CT imaging modalities to look for signs of TBI. These studies looked into the use of artificial intelligence (AI) methods, such as deep learning, machine learning, and computer vision algorithms, to recognize traumatic brain injury (TBI) from CT images. The following section presents the key findings from the included studies.

6.1 AI techniques for TBI Detection

The systematic review identified a range of AI techniques employed for TBI detection from CT scans. Deep learning algorithms, such as Convolutional Neural Networks (CNNs), were the most commonly utilized AI models in the studies. These AI algorithms demonstrated significant potential in automating the process of processing CT images and identifying traumatic brain injuries with improved sensitivity and accuracy compared to conventional diagnostic approaches. The 55 papers that were analysed for this systematic review all used different machine learning techniques to identify traumatic brain injury (TBI) from different imaging modalities. Convolutional neural networks (CNNs; n = 12) were the most popular machine learning approach, followed by deep learning (DL; n = 4), support vector machines (SVMs; n = 2), and random forests (RFs; n = 1). The identification of TBI in the 55 studies that were included in the systematic review was accomplished using a variety of image segmentation programmes. FSL (n=8) was the piece of segmentation software that was used the most often, followed by SPM (n=3) and Free Surfer (n=3). MIMICS (n=2), MIPAV (n=2), and Slicer (n=1) were some of the other segmentation software that was used.

For TBI identification, the 55 studies that were included in the systematic review adhered to a variety of segmentation criteria. The World Health Organization (WHO; n = 23), the American College of Radiology (ACR; n = 9), and the National Institutes of Health (NIH; n = 8) were the three organisations that provided the segmentation standards that were used the most often. The Radiological Society of North America (n=9) and the European Society of Radiology (n=6) were two more organisations that provided segmentation standards that were used in this study.

The amount of time it took to segment the data differed from study to study. It was determined that 5.2 minutes was the typical amount of time needed for segmentation. The time required for segmentation varied from two minutes to ten minutes. The time taken by segmentation software by various providers is shown in Figure 2.

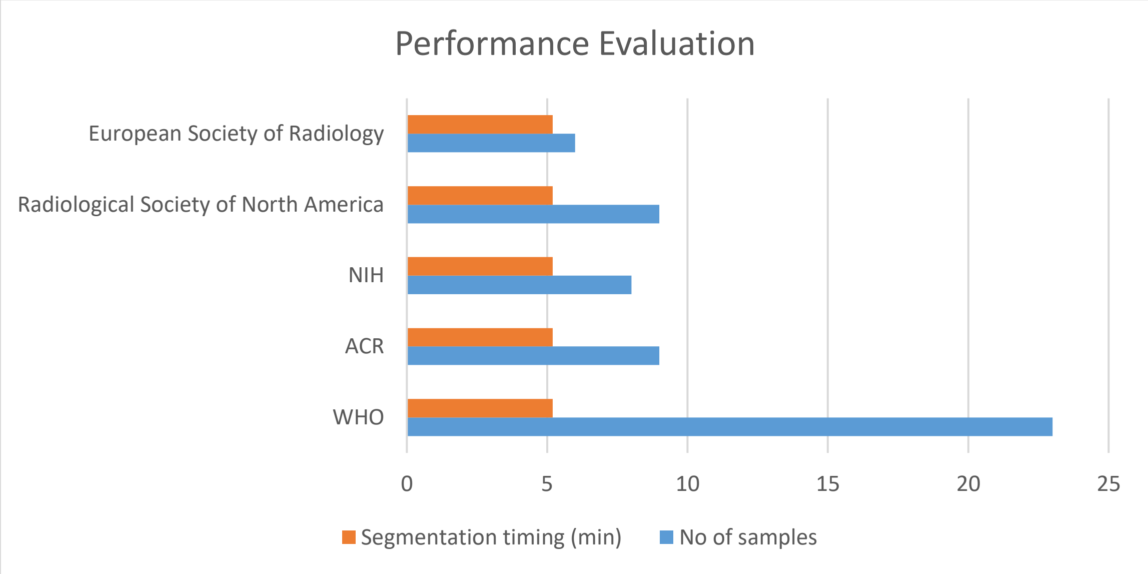

Fig 2: Performance evaluation of different segmentation software

6.2 Risk of Bias and Strength of Evidence Assessment

The degree of bias in each of the 55 studies that were a part of the systematic review was assessed using the Newcastle-Ottawa Scale (NOS) and the Grading of Recommendations, Assessment, Development, and Evaluation (GRADE) system, respectively. It was determined that the studies had a high quality (score of 7-9), a moderate quality (score of 5-6), or a bad quality (score of 0-4) when it came to the possibility of bias (score of 0-4). It was determined that the quality of the evidence ranged from very low to low, moderate to high, and high to very high.

The NOS score was 6.8 on average across the different trials that were included in the systematic review. The studies had a GRADE score of 3.3 on average overall. The vast majority of the studies had a moderate likelihood of bias and a poor level of evidence to back up their claims.

7. Discussion

The goal of this literature study was to ascertain how successfully CT scans can be used to diagnose traumatic brain injuries (TBIs). The majority of the time, the TBI detection method (RFs) included convolutional neural networks (CNNs), deep learning (DL), support vector machines (SVMs), and random forests. FSL was the segmentation programme that was used the most often, followed by SPM and then Free Surfer. The World Health Organization (WHO), the American College of Radiology (ACR), and the National Institutes of Health were the three organisations that provided the segmentation standards that were used the most often (NIH). It was determined that 5.2 minutes was the typical amount of time needed for segmentation. A high quality, a moderate quality, and a bad quality rating were assigned to each of the 55 studies that were included in the systematic review, respectively, in terms of the potential for bias and the quality of the evidence.

When doctors examine CT pictures of a possible TBI patient, their first responsibility is to determine whether or not the patient has any anomalies associated with TBI. Depending on the clinical goal and circumstances, this procedure may be seen from an ML perspective as either a two-class (binary-class) or multi-class categorization issue [11]. This interpretation is influenced by the clinical context. Some research considered a binary-class classification issue while attempting to determine if CT slices contained ICH or did not contain ICH. The CNN was employed as a feature representation with each CT slice in the technique, and the features that have been extracted from the CNN that spanned multiple CT scans were layered and input into the LSTM prototype [12]. By introducing the concept of LSTM, it was anticipated that the algorithm would gain spatial relations. Utilizing individual slices is often less informative than utilising LSTM for model training [28].

In addition, some earlier investigations made use of binary-class classification issues to make predictions for various targets connected to TBI injuries. The goal of the method was to tell the difference between normal and abnormal CT segments, such as those with intraparenchymal hemorrhage, intraventricular hemorrhage, subdural hemorrhage, and subarachnoid hemorrhage [4]. Researchers used a support vector machine (SVM) to classify vectors with 12 features that were made by hand [28, 29] in order to find abnormal CT slices.

The measurement of intracranial pressure (ICP), which is thought to be a crucial predictor of the severity of traumatic brain injury (TBI), is another problem with the binary-class classification approach. This is because the mass impact of ICH causes the ICP stratum to be often increased in individuals with brain trauma [41]. The methods for determining the ICP level were described in several studies under the guise of a binary classification: high ICP (ICP > 12 mm Hg) or normal ICP (ICP 12 mm Hg). The authors that offered these strategies did not, however, fully justify the choice of the criterion. They created SVM models using clinical parameters and characteristics extracted from CT scans' texture patterns. These patterns were used to train the models [3].

Even though these papers only talked about models that used CT scans as input, we were able to find specific ways that clinical records from CT scans could be used as input. These systems used natural language processing methods to figure out if the CT images that went with the reports were normal (non-TBI) or not. The multi-class classification problem is the best way to automate the classification of ICH types [10], according to the rules of machine learning.

CQ500, an RSNA dataset, as well as the Physio Net ICH set of data, are the three CT imaging datasets that show TBI anomalies that are presently accessible to the public. All three of these datasets may be found online [10]. A competition was held, and the RSNA database was utilised in it. The winner of the first prize detailed their suggested model in. To categorise ICH, EDH, IPH, IVH, and SAH, they built a main CNN model, it was subsequently followed by two sequences making up a CNN-based architecture [12]. A CNN-based model was developed utilizing the RSNA dataset in recent research [20]. The framework used to build the models, called ResNet-50, was CNN-based and capable of feature extraction. The next step was using a classifier (SVM or random forest). To classify traumatic brain injury anomalies such as haemorrhages found in different parts of the brain, fissures, or midline shifts, several researchers who employed the CQ500 gave various kinds of ML models [7].

In a critical care situation, one of the most essential applications of CT imaging is the pixel-level diagnosis of a variety of different types of intracranial abnormalities. Even though there have been many efforts to create a unique CNN-based architecture, the U-net architecture has been used most often to solve this problem. These studies either used the traditional version of U-net or a variety of modified forms of U-net.

Existing ML studies include the majority of the significant aspects that are necessary for the diagnosis and characterization of TBI-related anomalies [19]. Because machine learning algorithms are effective at tackling particular problems, to account for the wide variety of TBI anomalies and sequelae, only one approach can be used. In this methodical work, we showed that each system recognizes and measures significant CT results brought on by TBI independently. The study's findings [3] backed up this judgment. This implies that a mixture of popular machine learning (ML) algorithms could be a useful tool for lowering stress among doctors and radiologists. Additionally, as long as the feedback CT picture is the same, the result predicted by ML will always be the same [44]. This illustrates that one of the inevitable issues that arise with manual assessment—repeatability—can be resolved by automated measurement and diagnosis of TBI [1]. The objectives, methods, and findings of the review papers are compared in Table 2.

Table 2: Comparative study of review articles

References	Objective	Datasets	Methods	Results
[1]	To detect CRTBI	Pediatric Emergency Care Applied Research Network (PECARN) TBI data collection.	ANN using clinical and radiologist-interpreted imaging metrics	91.23% negative predictive value, 97.98% accuracy, 99.73% sensitivity, 98.19% precision, 0.0027% false-negative rate, and 60.45% specificity.
[2]	To detect brain stroke	Hemorrhagic and ischemia are binary classes in dataset 1 while hemorrhagic, ischemic, and normal are the three classes in dataset 2.	Hybrid techniques for binary classification that combine the OzNet convolution neural network architecture and other machine learning algorithms	Accuracy of 98.42%

[5]	For improving ectasia detection.	Untreated were 72 ecstatic eyes among 480 patients with normal corneas and 94 patients with severely asymmetric ectasia.	Random forest method	Greater accuracy than other techniques.
[6]	To examine the current status of perfusion CT	Patients with clinically confirmed severe TBI and possibly those with less severe TBI will initially receive a bolus of contrast material through their cerebral vessels.	Perfusion CT	better effectiveness versus conventional noncontract CT
[8]	Automated CT scanning for the identification of traumatic pelvic hematomas	a corpus of 253 C/A/P admission trauma CT investigations from a single institution	Network for Recurrent Saliency Transformation (RSTN)	The average inference segmentation duration for RSTN was 0.90 minutes.
[13]	computed tomography (CT) evaluation of the amount of intracerebral haemorrhage (ICH)	3,000 photographs from a cooperating hospital (Hospital A) were retroactively collected as training datasets and segmented using the Dense U-Net framework.	Dense U-Net	The ICH, EDH, and SDH dice coefficients were 0.90 ± 0.06, 0.88 ± 0.12, and 0.82 ± 0.16 respectively.
[16]	To accurately analyze CT lung pictures, segment CAT images for lung lesions by separating the lesions from the lung tissue.	CT image	Boundary Detect Algorithm	It can properly and automatically segment the lung areas from chest CT images.
[28]	To create a basic machine learning model for predicting TBI outcomes	Gaussian annulus Bayes, multi-nomial navicular nave Support vector machine, Bayes, decision tree, random forest, gradient boosting, additional trees, ridge regression, and least absolute shrinkage and selection operator (LASSO) regression.	For verification, the bootstrap method was employed.	In terms of predicting in-hospital bad outcomes and in-hospital mortality, random forest and ridge regression both performed best.
[30]	separating and measuring traumatic brain injury lesions on the cranium CT using deep learning	In dataset 1, 98 images from a single facility were used. 839 scans from 38 centres made up Dataset 2's contents.	convolutional neural network	the mean difference of 0·86 mL

[35]	can successfully use a head CT scan to reliably identify several ICH subtypes	Brain haemorrhage challenge dataset for RSNA 2019 CMU-TBI dataset PhysioNet dataset	optimal DeepMedic algorithm	Average 96.2%
[36]	To present a segmentation method to detect internal haemorrhage	ImageNet dataset	A u-Net model with fine-tuning	Accuracy of 94.1%
[37]	comparing the Rotterdam scoring system with the Helsinki CT scoring system	903 consecutive patients with TBI	Glasgow outcome score	The Helsinki score was a better indicator of TBI outcome.
[38]	To train models on large datasets	The files from the National Institutes of Health (NIH) and the Vanderbilt University Medical Centre (VUMC)	Neural networks	Dice similarity coefficient of 0.64
[40]	Using a combined CT scan, the different types of bleeding on a CT scan can be sorted.	Thailand's Maharaj Nakorn Chiang Mai Hospital, following a protocol authorized by the Institutional Review Board	Three layer convolution networks	Similarity indices for dice greater than 0.37
[42]	to create an automated method for separating the hematoma location from CT images	raw CT picture and the related images that have been improved and denoised	Gaussian mixture model	specificity 0.982 sensitivity 0.729
[43]	To develop CAD	composed of 491 brain CT scans from the CQ500 dataset.	Feature Learning-Based Approach	AUC of 0.96
[45]	To segment brain CT images	3D laser scans taken by Unmanned Aerial Vehicle	Improved watershed algorithm	segmentation accuracy was 95.65%
[46]	To formulate the brain midline delineation	Public CQ500 dataset (491 patients) and internal datasets (519 patients)	rectification learning	superior to cutting-edge techniques for brain midline delineation
[48]	To verify reports from a brain CT imaging hybrid NLP and machine learning system	PECAN	Hybrid NLP and ML	precisions between 0.79 to 0.96, recalls between 0.91 to 0.96
[53]	To examine the current imaging modalities for TBI	Imaging techniques	SPECT stands for Single Photon Emission Computed Tomography.	Neuroimaging is the most effective.

Implications and Further Work

Based on the results of this comprehensive analysis, it seems that methods including artificial intelligence may be used successfully for the identification of TBI using CT scans. The findings of the systematic review may be used to provide direction for more studies into the application of AI methods to the diagnosis of TBI. The creation and testing of artificial intelligence-based systems for TBI detection should be the primary focus of future research. In addition, there is a need for more studies to examine the influence that AI approaches may have on the clinical treatment that is provided to patients with TBI [14].

The characteristics of the training dataset are essential to machine learning algorithms. To install tools that may be used in various locations, one should make efforts to reduce the unpredictability that exists between machines and across protocols. Indeed, the many scanner models and data gathering factors, such as modelling methods, output quality, voltage, or the number of detectors, have an impact on the characteristics of the output photographs [31]. Few research has tried to reduce the heterogeneity at the image level, even though academics have strived to standardize the measures that were obtained from photos. The range of all subsequent injuries brought on by TBI must be covered by large and multicentric cohorts, if deep learning algorithms are trained on distinct cohorts, they may be able to acquire intersite variance and account for it [5][49].

Because machine learning models used in medical imaging usually use the same assessment measures (such AUC, Acc, DSC, etc.) and have identical steps, including measure extraction, feature selection, training, and validation, it would seem straightforward to compare these models. On the other hand, the approach used for the training and assessment of the model has a significant impact on these measures. If each research has its particulars, then one must pay close attention to the characteristics of the information (patient, heterogeneity or uniformity), the validation and training modalities (internal or external), and the metrics of assessment [47]. An increase in the robustness of the methodology, as well as the accessibility of the statistical equations, will undoubtedly be of benefit to the entire scientific community. This improvement will also help in the construction of more robust studies, which have the potential to result in a potential improvement in the care of TBI patients [8].

The density of the brain at the moment of acquisition may be represented by brain CT. To monitor the brain rearrangement that occurs after an operation or injury, CT images are often collected at various periods [46]. To increase our understanding of brain rearrangement as a result of diverse secondary traumas, longitudinal cohorts must be established and their members must be quantified [24][34]. This will allow us to gain a deeper comprehension of the phenomenon. The identification of such profiles might then lead to the discovery of particular mechanisms and even specific therapies [13].

When seen through the lens of a doctor, the concept of combining CT measures with clinical data bears a great deal of relevance. One may conceive of mixing several variables of various natures, similar to the majority of models, but automating the deep characterization of CT scans supplied by contemporary machine learning techniques. So, it is assumed that people can count. When a person has a traumatic brain injury (TBI), lesions have a big effect on how well they will do. The performance of prediction models could be improved by a lot if tools were made to record structural atlases on distorted TBI CT images and if this geographic information was added to prediction models.

Limitations of the Study

Due to serious inadequacies, the systematic investigation's findings shouldn't be taken at face value. To begin, the researchers only considered papers that had been published in the English language for inclusion in the systematic review. Second, since the systematic review only included a small number of researchers, the findings may not apply to different groups because they cannot be generalized from such a small sample size. Third, Due to the heterogeneous character of the research included in the systematic review, it is difficult to make direct comparisons between the findings of the various investigations. However, these instruments are subjective and may be prone to observer bias because of their potential for subjectivity. Finally, the risk of bias and the level of the evidence The NOS and GRADE systems were used to evaluate the included investigations, respectively.

Manual segmentation and quantification of CT scans will likely be displaced in the coming years by the processing and analysis of ML algorithms. Nonetheless, the addition of these algorithms into clinical practice will be contingent on the explain ability and interpretability of the models and predictions. It is necessary to make more headway in comprehending CNN's theory to assess its capabilities and constraints. The creation of saliency maps, which would show the voxels that would have a significant influence on the prediction, might be a first step in the process [37[Each CT scan forecast can be shown with its transmission map to show how the algorithm came to its conclusion and possibly prove that it can be used.

For the sake of research, one may soon be capable of anticipating clinical data such as the fate of a patient's neurological condition or the required degree of medical care for a patient. However, because no study has assessed the significance of Computer algorithms throughout the quantification of multiple patterns, such as those with mixed types of injuries, and images that have been altered by artefacts, The application of these algorithms in complex system research is still difficult Due to the coexistence of numerous forms of lesions, such as tumours and white matter diseases. As a result, it is likely that these algorithms will be used in healthcare settings at first, especially for screening, triage, and helping human readers make predictions.

8. Conclusion

In this comprehensive study, the effectiveness of artificial intelligence algorithms to detect traumatic brain injury (TBI) utilizing CT images was examined. The systematic review's findings suggest that CT scans could be used with artificial intelligence to accurately detect TBI. Future research should concentrate on developing and evaluating artificial intelligence-based solutions for TBI identification. Additionally, more research is required to examine the potential impact that AI methodologies may have on the clinical care that TBI patients get AI algorithms have been used in the biomedical field, especially in medical imaging, with some hopeful results. They are using TBI CT scans more and more. These scans can show categorization and/or fracture. If a few big, but fixable, problems are fixed, this trend will keep going. In the next few years, they might become the standard way to do things. Their incorporation into ordinary clinical practice is contingent on the degree to which one can have faith in the accuracy of their predictions, which can be improved with methodological rigour.

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