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A Review on Deep Learning and Traumatic Brain Injury

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Abstract

Traumatic Brain Injury (TBI) disrupts the brain's usual functioning and can lead to temporary or permanent neurological defects. Detecting and treating TBI at an early stage can considerably improve the recovery time and avoid serious complications. Doctors rely on medical imaging to diagnose TBIs. As against the manual detection methods which may overlook subtle patterns resulting in inaccuracy and inconsistency, the computational methods can continuously adapt based on new data which improves the prediction model's accuracy. Specifically, deep learning techniques are capable of extracting useful features from unstructured data such as medical images, without any need ad manual feature engineering However, the existing review papers discuss TBI detection using DL methods only in addition to the traditional and ML methods and fail to cover the vast variety of the recent DL algorithms. This review exclusively focuses on DL algorithms for TBI detection and encompasses cutting-edge DL models used in this domain. The choicest collection of articles unveils the potential of deep neural networks to process different types of inputs including numerical data EEG, CT and MRI scan images. This comprehensive overview offers a one-stop solution for the various research interest groups to get an understanding of the different techniques used and acquire valuable insights to conduct research in different disciplines ranging from image processing to advanced deep neural networks.

Keywords: Artificial Neural Network (ANN), Brain Hemorrhage Classification based on Neural Network (BHCNet), Convolution Neural Network (CNN), Deep Learning (DL), Multi-Layer Perceptron (MLP), Recurrent Neural Network (RNN).

Introduction

Traumatic Brain Injury (TBI) results from a sudden and forceful impact to the head or body usually caused by external forces (1). This causes a disruption to the brain's normal functioning and its severity can vary from mild to severe resulting in either temporary or permanent neurological defects (2). It can cause numerous complications, including seizures, nerve injury, blood clots, and constriction of blood vessels, stroke, coma, and brain infections (3). TBI is a widespread concern for health, leading to high rates of mortality on a global scale. According to the data provided by the IHIF, India holds the highest global incidence of brain injuries (4). Over one and half million people in the US suffer from TBI, with higher vulnerability seen among adolescents aged 15 to 19 and adults aged 65 and above. These age groups are more prone to sustaining such injuries compared to other demographics within the population (5). The most accurate documentation for diagnosing a traumatic brain injury is typically obtained either at the time of the injury or within the initial 24-hour window following the incident. This early assessment period is crucial for understanding the extent of the injury and initiating appropriate treatment strategies (6). TBI can lead to issues with numerous brain functions, and some may be temporary but others may be long lasting. Some of these problems do not appear until days or months after the injury. But early detection of TBI might be lifesaving. Hence it is very important to devise computational methods which can predict TBI as quickly as possible, as against the physical methods which are time consuming (7). Though manual detection methods such as Glasgow Coma Scale (GCS), assessment tools like Providers Clinical Support System (PCSS) and length of coma were being used extensively for predicting TBI in the past, they can be inconsistent some-

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times whereas computational methods are quite consistent in their analysis leading to accurate and faster diagnosis of TBI. Furthermore, the advent of diagnostic tools such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans has resulted in the availability of a substantial amount of input data with which the automated algorithms can be trained, for better recognition of TBI patterns whereas manual detection methods may overlook subtle patterns resulting in inaccuracy and inconsistency. Lastly, the computational tools can continuously adapt based on new data which improves the accuracy of the prediction models. There are several review papers summarizing the various methods for TBI detection. Commonly used Machine Learning (ML) algorithms for TBI detection are logistics regression, k-nearest neighbors (KNN), naive Bayes and Support Vector Machine (SVM) (8). A comprehensive study reported that ML methods outperform traditional methods for prolonged mechanical ventilation (PMV) risk prediction in TBI patients (9). Owing to the ability of deep learning techniques to excel in extracting unstructured data features like medical images, without any need for manual feature engineering, there are review papers highlighting the success of ML and DL in detecting intracranial hematoma, an elevated intracranial pressure, and midline shift in CT brain images (4), in automating TBI image interpretation, improving clinical management, and integrating precision medicine (10) and in radiology workflow optimization (11). With the availability of large, labeled datasets and computational resources, it is evident that Deep Learning (DL) models offer superior performance (12). However, the existing review papers discuss TBI detection using DL methods only in addition to the traditional and ML methods and fail to cover the vast variety of the recent DL algorithms. This review exclusively focuses on DL algorithms for TBI detection and covers state-of-the-art DL models used in this domain that can help the readers get an understanding of these techniques and acquire ideas for future research. TBI can be predicted or classified using inputs obtained from various brain imaging techniques. In this review, we have grouped the papers based on the input techniques used. The first one is EEG or electroencephalogram. An EEG test gauges the brain's electrical activity using small metallic electrodes attached to the skull. Electrical impulses are used by brain cells to communicate, and they are always active, even while a person is sleeping. It counts as one of the diagnostic tests for epilepsy, brain disorders and traumatic brain injuries. The second input technique is called CT. A narrow beam of x-rays is directed at the patient which is quickly revolved around the body in this computerized x-ray imaging procedure, providing signals that the machine's computer processes to create cross-sectional images. Another important source of input data is MRI images. It is an imaging technology that generates 3-D anatomical images. It is based on detecting changes in the direction of the rotating axis of protons present in the water that makes up biological tissues. We have the 'others' section which discusses the input techniques other than EEG data, CT and MRI images. These techniques include widefield imaging, recordings of cortical activity using specialized imaging, detailed brain strains using measured kinematics, mel-frequency and audio recordings. The organization of this paper is as follows: the following section provides a summary of the sources of articles considered for this review. Following that, papers that employ DL approaches to process EEG data are investigated and presented. The section that follows comprehends the papers that use CT images as input. Following that, DL models that work on MRI images were analyzed and presented. Subsequently, DL algorithms applied to other input data that do not fall into any of the above categories are discussed. Finally, conclusions from this review and future research directions are provided.

Methodology

We have systematically reviewed 88 research papers published from 1994 to 2023, to analyze various deep learning methods which helped in predicting Traumatic Brain Injuries. From Figure 1, it can be seen that the majority of the papers were particularly from the years 2020-2022 to capture the latest advancements in the field. There are 13 papers from the year 2023, 25 papers from 2022, 20 papers from 2021, 15 papers from 2020 and 23 papers from the years 1994 to 2019. As shown in Figure 2, the papers included are from renowned publishers such as IEEE, NCBI, PubMed, Elsevier, Research Gate, Springer and MDPI. Few papers have also been included from NINDS and

PLOS. Our review is categorized based on the following input techniques: 1) EEG data 2) CT scans 3) MRI images and 4) other input techniques.

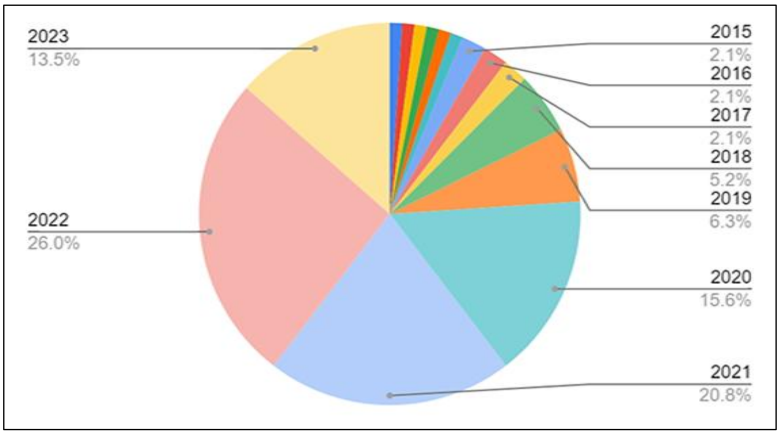

Figure 1: Year-wise Count of Articles

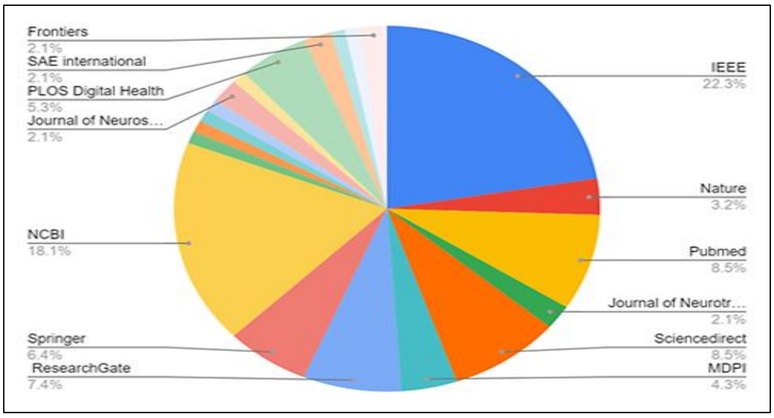

Figure 2: Count of Articles from Different Publications

Diagnosis with EEG Data

Traumatic brain injury (TBI) causes disruptions to the brain's normal functionality due to trauma's impact on the neural connectivity. Electroencephalography (EEG) is a type of neuroimaging technique that monitors the brain's electrical activity. It functions on the principle of brain waves (brain's electrical impulses) reflecting the communication between neurons eventually providing valuable insights into brain function and activity. This type of input data can detect abnormalities in the brainwaves including fluctuations in frequency, amplitude or patterns of electrical activity. Post TBI, EEG has a significant part in both identification and cure by aiding in preparation, assessment, monitoring, and understanding of brain function alterations. Table 1 summarizes the different deep learning models that have been employed in the literature to work with EEG data.

CNN

A novel classification architecture was proposed for distinguishing TBI patients of mild to moderate category from healthy individuals utilizing a dataset comprising EEG recordings (age range 18-65). This dataset was provided by Universiti Sains Malaysia Hospital, located in Kelantan, Malaysia (13, 14). The architecture used CNN and ECOC-SVM. Two similar works carried out using CNN, processed 63×100 input matrices (13) and 63 x 1000 input matrices (14) respectively, with six 3×3 filters, using ReLU activation. Batch normalization was applied after the convolutional layer. A 2 × 2 average pooling layer with a stride of one received six feature maps, each measuring 63 × 100. The average pooling layer subsampled the feature maps to six 31 × 50 maps. The six 31×50 feature maps were fed into fully connected layers (Layer 3 and 4, 128 neurons, and Layer 5, three neurons). Training employed a fixed learning rate (0.001), an ADAM optimizer, L2 normalization, and mini-batch of 16. This model stated in the papers determined mild (between 9 and 12) and moderate (between 14 and 15) TBI as per the Glasgow Coma Scale (GCS). 99.76% of exceptional accuracy of classification was recorded for CNN ECOC-SVM. A comparative analysis resulted in the following order of accuracies: CNN ECOC-SVM>Naive Bayes > SVM(PSD) > Adaboost > SVM (power). A comparison was done between machine learning models, featureless models, and DL models to identify those providing improved performance in differentiating TBI, stroke, and normal states using EEG data (15). The EEG dataset was taken from The EEG Corpus from Temple University Hospital. The dataset consisted of 14,987 participants with 26,846 clinical sessions of EEG, summing to 69,652 files of EEG. Several featureless DL models such as LSTM, TMN and Short-time Fourier Transform (STFT) were also assessed in the study. The ADAM optimizer with initial training rate of 3 × 10^ (−4) was used. As a result, the precision was 77.9%, while the accuracy of validation was 68.9% between the TBI/Stroke/Normal categories. The area under receiver operating curve (AUCROC) for feature-based models was 0.85, whereas it was 0.84 for featureless models. An automated approach was developed for classifying non-severe TBI patients using EEG and DL (16). A CNN, employed for extraction of features from resting state EEG data. These features were then utilized to train hidden Markov models (HMM) for the classification of non-severe TBI patients. A classification accuracy of 85.5% was achieved by the proposed architecture. Other than prediction and comparison, many studies have also been conducted to learn about the specifics of TBI. One such study developed the ECI using a CNN based on diverse datasets (17). The ultimate dataset comprised of 15 UWS (Unresponsive Wakefulness Syndrome) patients (had severe traumatic brain injuries), 15 MCS (Minimally Conscious State) patients, and 4 MCS*(UWS patients that show similar brain activity to MCS patients). The TMS–EEG data included participants during sleep, anesthesia, disorders of consciousness in patients, and resting-state EEG data. The CNN architecture included five convolutional layers with 2D filters, max-pooling layers, and a softmax layer. ECI, calculated by averaging interclass probabilities, effectively discriminated altered states of consciousness. The study demonstrated the ECI's effectiveness in assessing arousal and awareness in various conditions.

MLP and RNN

The automatic observation of EAs in patients with TBI using continuous EEG data from the EpiBioS4Rx study was investigated (18). The dataset included EEG recordings from 4 male TBI patients, with a mean age of 45.25 and a mean GCS of 8.25 upon reaching the department of emergency. Two deep learning models were proposed for EA detection: a RNN and a MLP. The RNN was designed to capture temporal aspects and consisted of two hidden layers with ReLU activation and LogSoftmax for output. Raw EEG data without preprocessing is segmented into 5-second epochs and used to balance computational complexity and training sample size. RNN performed better than the Multi-Layer Perceptron in both two-class and four-class segmentation tasks.

CNN for TBI Detection in Mouse

The above papers used human EEG data for their studies. However, there is a similarity in nervous system organization and function between mammalian species and rodents, making them a favored system for studying analogues of human neurological disease. The focus was on diagnosing TBI in mice (aged 10 weeks, 25 grams, male) by classifying them into three groups: mild, moderate, and severe (19). The dataset of 9 mice employed was a recording spanning a full 24 hours comprising EEG dataset of a mouse TBI model, with just four mice having TBI. The EEG features were inputted into two sets of conv1D-pooling pairs, culminating in a dense layer followed by a softmax layer. Each convolution utilized a length of 4, kernels numbered to 16, incorporating max pooling with a stride of 2. The last dense layer consisted of 40 nodes. Training employed categorical cross-entropy as the cost function, optimized with Adam optimizer and supplemented with regularization of L1. Results proved that the Convolutional Neural Network outperforms rule-based methods for sleep stage analysis due to its temporal insight. Rule-based methods showed competitive accuracy with CNN for wake stage analysis. However, CNN achieved the highest accuracy of 92.03%. While the above paper categorized TBI severity, another study examined how mild traumatic brain injury (mTBI) affected mice's sleep patterns, categorizing them into four groups: sham and mTBI wake, sham and mTBI sleep (20). These used Electroencephalogram data and a CNN model to classify these patterns. The dataset included 11 mice - 5 in the mTBI group and 6 in the sham group, EEG data was captured at 256 Hertz, resulting in 22,118,400 timesteps/mouse over 24 hours. Training consisted of 50 epochs with the Adam optimizer and default parameters. Global MaxPool1D downsampled its input by taking the highest value across the dimension of time. The final dense layer followed by softmax activation function performed the class prediction. Different results were obtained while combining different features: the feature dimension, width of EEG epoch and the number of filters. An accuracy of 81.5% was obtained when the epoch length was 64s. Keeping the epoch length 64-s (RS data arrangement) and varying the filters and f_dim (64 and 8 respectively), the best accuracy obtained was 82.6%, and for SA data arrangement, the best value from cross-validation folds was 57.1%. Deploying these results on an RPi model or HPC, an accuracy of 82.1% was obtained. A model for detecting mild TBI (mTBI) was developed utilizing Electroencephalogram data collected from a mouse model of lateral FPI (21). Mice were subjected to fluid percussion injury and EEG/EMG implantation. Animal tests (two groups: TBI and sham) were carried out on Ten-week-old male mice of C57BL/6J, weighing 25 grams. The features were sent to sixteen filters in a 1-D CNN layer with a size of 4 kernels and function of ReLU activation by the CNN. Subsequently, a MaxPooling layer with a stride of two reduced the signal length by half. CNN performed better than K-Nearest Neighbors (KNN) and its performance slightly increased as the epoch length increased. A model was developed to recognize TBI and automatically evaluate sleep stages using an Electroencephalogram of one-channel input (22). This dataset was obtained from the United States Centres for Disease Control as a component of a study that included eleven adult male mice divided into 2 groups: Sham and mTBI. Two different models were deployed on Raspberry-Pi—CNN and XGBoost. The EEG epochs were queued for processing to go through preprocessing, feature extraction, and classification. The results on the Raspberry Pi (RPi) were consistent with those of a HPC at various epoch lengths (16 s to 64 s). Accuracy for XGBoost showed a slight decrease (0.01%) with longer epoch sizes, while CNN's accuracy improved by approximately 7 percentage points with larger epochs.

Table 1: Deep Neural Networks for TBI Detection with EEG Data

Authors	Dataset	Architecture	Technique	Performance
Lai *et al.,* (13)	Hospital Universiti Sains, located in Kelantan, Malaysia. 36 EEG recordings	Fully connected layers Average pooling layer ReLU activation layer L2, batch normalization Adam optimizer	CNN ECOC-SVM	CNN ECOC-SVM > Naive-Bayes > (PSD)SVM > Adaboost > (power)SVM
Lai *et al.,* (14)	Hospital Universiti Sains, located in Kelantan, Malaysia. 30 EEG recording (15 healthy and 15 mTBI patients) recorded using 64 channel systems	Convolutional layers - 6 Pooling layers - 2 Fully connected layer - 1	CNN	Average classification accuracy - 72.46%. It consistently outperforms four other machine learning approaches: Naive Bayes, AdaBoost, SVM (MRMR), and SVM (power)

Caiola *et al.,* (15)	TUEG Version 1.2.0. It included 14,987 patients with 26,846 clinical sessions of Electroencephalogram, resulting in 69,652 Electroencephalogram files (about 1,643 GB).	ADAM Optimizer Learning rate - 3×10^{-4} Epochs - 400	Models used: TMN, LSTM, STFT	AUROC with feature-based models: 0.85 AUROC with featureless models: 0.84 Validation accuracy - 68.9% Precision - 77.9%
Lai *et al.,* (16)			CNN	classification accuracy of 85.5%.
Faghihpirayesh *et al.,* (18)	EEG recordings of 4 male TBI patients	2 hidden layers ReLU activation LogSoftmax for output.	MLP and RNN	Model performance was assessed using precision, sensitivity, F1-score, and accuracy metrics. RNN performed better than the MLP in both two-class and four-class segmentation tasks.
Vishwanath *et al.,* (19)	eC57BL/6j mice from Jackson Laboratory. 9 mice were used, in which 4 mice actually had TBI and 5 were shams.	Conv1D-pool pairs - 2 Dense layer (40 nodes) and softmax layer Kernels - 16 Adam Optimizer	CNN	CNN accuracy: 92.03%. CNN outperforms rule-based methods (SVM, KNN,DT and RF)
Sutandi *et al.,* (20)	The Jackson Laboratory. 22,118,400 timesteps per mouse over 24 hours.	Adam optimizer 1D convolution layer Global MaxPool1D Rectified Linear Unit (ReLU) activation Batch Normalization layer applied.	CNN	Accuracy : 81.5% (epoch length - 64s) Best accuracy : 82.6% SA data arrangement (best value) : 57.1%. Deploying on an RPi model or HPC : accuracy - 82.1%
Vishwanath *et al.,* (21)	EEG data was collected from lateral FPI of a model mouse. 24 hour recording sampling rate: 256 Hz collected from each animal (TBI and sham).	1D convolution layer ReLU activation functions MaxPooling layer Batch-normalization layer L1 regularization Adam optimizer	CNN	CNN performed better than rule-based models. Average of variances for cross-validation techniques: CNN : 0.92% KNN3 : 1.93% KNN5 : 1.94% KNN7 : 2.10%
Dhillon *et al.,* (22)	U.S. Centers for Disease Control.	Two implementations on RPi:	Raspberry-Pi CNN and XGBoost	Accuracy for XGBoost showed a slight decrease (0.01%) with longer

	1. CNN model 2. XGBoost (gradient decision-tree boosting model)	epoch sizes, while CNN's accuracy improved by approximately 7 percentage points with larger epochs.

Diagnosis with Computed Tomography Images

Computed Tomography (CT) scans are critical in the detection and assessment of TBI. When a patient experiences head trauma, CT imaging is often one of the primary diagnostic tools used by healthcare professionals. CT scans are indispensable tools in the detection and evaluation of TBI. They provide critical information for timely and effective decision-making in emergency and clinical settings, ultimately contributing to improved outcomes for TBI patients.

ANN and Other Variants

Data from the PECARN-CITBI study, which included children under the age of 18 who came to twenty-five North American emergency rooms within twenty-four hours of sustaining a head injury from June 2004 to September 2006, was investigated (23). After preprocessing, it contained 15,271 entries and 85 characteristics, which included data labels. These features included information such as patient identifiers, physician details, data labels, clinical demographics, and Computed Tomography scan results being used on the models RF, deep ANN and shallow ANN. It combined a Random Forest (RF) feature selector with a shallow Artificial Neural Network (ANN) having three layers: input, hidden (30 sigmoid neurons), and output. Additionally used, a deep ANN with five layers, including three hidden layers with ReLU neurons. The paper summed up that ANN algorithms work well in identifying the existence of mTBI in the pediatric population. The study relied on data from the PECARN study, which prospectively investigated children with CRTBI (24). The PECARN TBI study enrolled individuals aged under 18 who had experienced non penetrating head trauma and had presented at the emergency department between 2004 and 2006, with a specific focus on classifying head CT imaging upon admission. Out of the 14,969 patients who underwent head CT scans, 12,902 had complete imaging data available for analysis. The study employed a 2-layer feed-forward ANN with 11 sigmoid neurons in the hidden layer and softmax neurons in the output layer. The softmax activation function was utilized in the resultant layer of neural networks for classification tasks because it turned raw output scores into probabilities, making it appropriate for multi-class classification. A retrospective cohort study was orchestrated to develop an ANN predictive model for posttraumatic epilepsy in TBI patients (25). The purpose was to identify high-risk patients for improved management. The study employed a 3-layer multilayer perceptron ANN model, utilizing 21 independent variables. The training cohort comprised 1301 patients from West China Hospital, and testing was done on external cohorts from Shang Jin Nan Fu Hospital (with a sample size of 421) and Sichuan Provincial People's Hospital (with a sample size of 413). The input dataset included demographic, clinical, and radiological data of TBI patients diagnosed between 2011 and 2017. The ANN model exhibited a mean AUC of 0.907 in the training cohort. Testing cohorts showed AUCs of 0.867 and 0.859, with sensitivities of 0.83 and 0.80, and specificities of 0.80 and 0.84, respectively. The architecture involved a back-propagation learning algorithm, and model development included 5-fold cross-validation. The evaluation parameters were PPV, NPV, correctness, sensitivity, specificity, AUC and average precision. Brier scores were calculated to calibrate the model. The aim of the study was to tackle the overuse of Computed Tomography scans in cases of mild TBI by employing a deep ANN model to reproduce the clinical rule of the PECARN within a population of pediatricians (26). The study made use of data gathered from the PECARN study from 2004 to 2006, which contained a total of 14,983 patients below the age of 18 with Glasgow Coma Scale (GCS) scores greater than 14 for those with head CT reports. The DANN model was trained using the PECARN rules' clinical features (PECARN-A for age lesser than 2 years, PECARN-B for age greater than 2 years). In addition to this, an instance hardness threshold technique was used to predict whether the pediatric patients would need CT by the use of 5-fold cross-validation. The DANN model showcased sensitivity of 98.6% and specificity of 99.7% for determining the requirement for CT, surpassing the PECARN rules combined in the phase one. In phase two, the DANN model outdid both PECARN-A as well as PECARN-B rules when keeping into account predictors for each age group independently, achieving higher sensitivity and specificity in contrast to the original clinical rule. The study concluded that the DANN model showed excellent specificity and comparable sensitivity for reproducing the PECARN clinical rule in determining pediatric patients needed CT after mTBI.

DNN, SNN and LRNet

A study was conducted to predict outcomes after TBI in nations with low to moderate incomes using machine learning (27). Three models were developed: a DNN, a shallow neural network, and an elastic-net regularized logistic regression. These models used 13 readily obtained clinical factors to predict whether patients would have good or bad outcomes upon hospital release. The DNN model performed much better than other models in the area under the receiver operating characteristic curve. Whereas, the shallow neural network model excelled in the area under the precision-recall curve. The elastic-net LRnet demonstrated noninferiority to the neural networks in several comparisons. The research aimed to provide cost-effective and scalable prognostication solutions for TBI care in resource-constrained settings. Predictors were opted depending on data accessibility and neurosurgeon consensus, focusing on variables easily collected during admission in low-resource settings, including age, GCS, vital signs, pupillary reactivity, mechanism of injury, and other binary categorical variables.

CNN

A CNN-based algorithm was developed to quantify and detect different lesion types (28). The first dataset comprised of 98 scans whereas the second dataset consisted of 839 scans collected from 38 different centers, with 184 scans assigned for training data and 655 for the testing data. The CNN algorithm was utilized to fragment a new dataset of medical scans. This was followed by manual correction of the second dataset. A subgroup of these scans was used to train last CNN for multiclass lesion segmentation. CNN's lesion detection performance was externally validated on 500 patients. CNN-derived lesion volumes showed mean differences of 0.86 mL (with a 95% confidence interval of -5.23 to 6.94) for intraparenchymal hemorrhage, 1.83 mL (with a 95% confidence interval of -12.01 to 15.66) for extra-axial hemorrhage, 2.09 mL (with a 95% confidence interval of -9.38 to 13.56) for perilesional oedema, and 0.07 mL for intraventricular hemorrhage compared to manual reference measurements. DeepMedic and EfficientNet were used to address the critical issue of TBI detection (29). A dataset of 25,000 CT scans with 5 ICH subtypes, totaling 755,948 slices, was split into 740,829 training and 15,119 test slices. It included 82 CT scans (46 male, 36 female, avg. age 27.8) with 34 slices each. Another dataset had 30,000 slices, each 1.5 mm in thickness, from DICOM CT scans among which 143 were of normal brains and 178 were of TBI. The method combined EfficientNet-B2, DeepMedic, and a quantitative assessment algorithm, adjusting intensity windows (Brain, Subdural, Soft tissue). The system had 11 neural network layers and used an optimized DeepMedic model for CT scan multi-class segmentation. It outperformed U-Net and UNet++ and was suitable for multi-class tasks. It achieved 98.62% accuracy on the CMU-TBI dataset, with 96.54% accuracy for Subdural Haemorrhage (SDH) classification and a 96.21% mean accuracy for all hemorrhage subtypes. The significant issue of brain stroke was tackled in a study (30). It involved categorizing the brain Computed Tomography scans into three groups: ischemic stroke, hemorrhagic stroke, and normal cases. They introduced an innovative CNN model with image fusion and a 13-layer architecture. The first dataset was received from the Himalayan Institute of Medical Sciences, Dehradun, India and was split into 20% for testing data and 80% for training data. On the contrary, the 2nd experiment utilized a ten-fold cross-validation on the dataset. The classification accuracy of the proposed CNN model was, reaching 98.33% in the initial experiment and 98.77% in the second. The study extended its investigation to Dataset 2 which encompassed three categories: ischemic stroke, hemorrhagic stroke, and normal cases. The dataset consisted of 900 CT scan images from 74 people. The CNN model from the first experiment achieved a classification accuracy of 92.22%, outperforming the AlexNet and ResNet50. The second experiment, utilizing a ten-fold cross-validation, further validated the effectiveness of the CNN model, resulting in an accuracy of 93.33%. Limited data availability for medical imaging model training, due to constraints on transferring protected health information, was addressed in a study (31). They performed CT brain hematoma segmentation using datasets from the National Institutes of Health and Vanderbilt University Medical Center. Three distinct neural networks were trained: one on the data from NIH, one on the data from VUMC, and the third, a multi-site model alternating between NIH and VUMC data. The multi-site model demonstrated superior performance with a Dice similarity coefficient of 0.64. There was a 5% improvement in the segmented hematoma volumes over the single-site models, achieving a correlation of 0.87 with manually segmented volumes. The architecture was based on a 2D version of the Inception Net, incorporating convolution layers, ReLU activation, an adapted Inception Module, and final convolution with sigmoid activation. Training involved convergence based on a 1×10^{-4} loss improvement criterion over 10 epochs, using a learning rate of 1×10^{-4} and the Adam optimizer, with the continuous Dice coefficient as the loss function for binary segmentation masks. The study concluded that multi-site learning enhanced model generalization and segmentation accuracy. A Computer-Aided Diagnosis algorithm for classifying TBI in CT images was presented in a study (32). The proposed algorithm, VGG-SE-PCR, integrated a novel neural network structure combining VGG-S, the Squeeze and Excitation (SE) module, and the Pixel-wise Correlation Retaining (PCR) module. Leveraging transfer learning to address limited datasets, the method achieved a classification accuracy of 89.3% on 636 brain CT images. Ablation experiments validated the efficacy of the SE and PCR modules, and comparative analysis showed superior diagnostic accuracy when compared to advanced methods for CT images of TBI patients. The primary focus was on improving the accuracy of predicting outcomes for individuals with TBIs, a crucial factor influencing treatment decisions, patient care, and post-treatment follow-up (33). Important factors that have been found to be critical for predicting the outcomes of traumatic brain injuries include age, motor and pupil response, hypoxia, hypotension, and CT scan results. An expanded TBI outcome prediction model was fed lesion volumes and the information that went along with them. While comparing the efficiency of the proposed features with the established Marshall score, the automatically obtained quantitative CT features showed superior predictive potential compared to the Marshall score. The inclusion of automatic atlas alignment showed the importance of frontal extra-axial lesions as indicators of unexpected outcomes. A postresuscitation Glasgow Coma Scale score of 8 or below indicated severe TBI, which posed a serious risk with mortality rates as high as 40%. The possibilities of DL in prognostication for severe traumatic brain injury were investigated in a study (34). A customized CNN model architecture with an AlexNet backbone was utilized. Sub volumes from every CT scan, which covered the midbrain to the lateral ventricle, made up the input. With exception of the last completely connected layer, transfer learning was used for trainable layers. A customized curriculum learning technique was used for training. The fusion model, combining CT scans and clinical data, outperformed IMPACT in predicting both mortality (AUC 0.92) and unfavorable outcomes (AUC 0.88) in the UPMC cohort. The fusion model maintained predictive power for mortality (AUC 0.85) in the more severe TRACK-TBI cohort but showed lower performance in predicting unfavorable outcomes. The focus was on the timely diagnosis of intracranial hemorrhage (ICH), a medical emergency associated with severe disability (35). The primary dataset came from the 2019-RSNA Brain CT Hemorrhage Challenge, providing more than one million images from 25,272 examinations. A CNN classifier trained on 2D image slices was employed to determine the presence of ICH and its subtypes. Three backbone networks—SE-Resnext101, Densenet169, and Densenet121—were utilized for the CNN classifier. Performance evaluation on the RSNA test data showed robust results, with an ICH detection accuracy of 0.988 (AUC). Different sensitivity and specificity for individual ICH subtypes was exhibited, with the highest accuracy of detection for Intraventricular Haemorrhage (IVH) (AUC: 0.996, specificity: 0.974, sensitivity: 0.975) and the lowest for SDH (AUC: 0.983, specificity: 0.932, sensitivity: 0.946). The algorithm's validation on external datasets, PhysioNet-ICH and CQ500, demonstrated consistent performance with AUCs above 0.94 for most subtypes. A unique model of DL based on ICH diagnosis and classification was developed in a study (36). It utilized optimal image segmentation together with an Inception Network. Below the age group of 72 years, head CT scans of 82 patients were included in the dataset. For the image segmentation, KT-EHO algorithm was applied to indicate the diseased portions. Recognition and categorization of ICH were done using Inception v4 optimized by Adagrad (AG) optimizer. Finally, an MLP model composed of the 3 layers: input, hidden, and output layers was used as a classifier to identify the various ICH classes. For the CNN architecture, a feature map was constructed for the initial layer. The kernel size was 5x5 and stride was set as 1. Followed by that, convolution layers, activation layers, pooling layers, FC layers and SoftMax layers were applied one after the other. In comparison with models like WA-ANN, SVM, U-Net, WEM-DCNN and ResNexT, DL-ICH model had outperformed with a precision of 95.26% and an accuracy of 95.06%. A novel method referred to as BHC, based on Neural Network, was proposed in a study (37). The dataset used for this consisted of 200 CT scan images, evenly distributed between cases of those having brain hemorrhage and those with non-brain hemorrhage. Initial steps involved image preprocessing, which included resizing the CT scan images to a standardized 128x128 pixel size and flipping. The architecture of the proposed BHCNet involved convolutional 2D layers, max-pooling layers, global average pooling layers, and dense layers. The aim of this design was to make it easier to extract features from CT scan images which is essential for classifying cases of brain hemorrhage. Balanced and imbalanced datasets were examined by the researchers. The unbalanced dataset strategy entailed boosting the number of positive cases, more specifically the brain hemorrhage instances in order to direct the model's attention towards false negatives. The outcome showed the productiveness of the proposed CNN model. For a balanced dataset, the CNN achieved an impressive 95% accuracy after 24 epochs, demonstrating high precision (90.90%), sensitivity (100%), specificity (90%), and an F1-score of 95.23%. The metrics showed the efficiency of the model for accurate classification. The model effectively eliminated false predictions, particularly false negatives, contributing significantly to enhanced diagnostic accuracy with 100% sensitivity, 95.5% specificity, 95% F1-score, 100% accuracy and 95.54% precision.

Other Variants of CNN

A completely automated technique that measured the volume of the basal cistern and the midline shift while accurately estimating the acute intracranial lesion volume was proposed in a study (38). The data from the CENTER-TBI study was used, which involved around 5000 patients from various hospitals. The data was divided into three groups based on patient care paths: ER, admission, and ICU. Different CT scanners with varied imaging parameters were used. U-Net–based CNN was used for the segmentation of acute intracranial lesions in TBI patients. The focus was on validation and performance of this automated method using a multi-center dataset from the CENTER-TBI study. The study concluded that the proposed automated framework, "icobrain" utilizing a U-Net–based CNN, is a reliable tool for quantifying CT features in acute TBI cases. The method accurately segmented and estimated volumes of intracranial lesions, basal cisterns, and midline shifts on CT images. Validation using a multi-center dataset showed good agreement with expert reference segmentations, suggesting its potential value in clinical evaluation and large-scale TBI studies. The goal was to identify and evaluate intracranial bleeding, a serious side effect of TBI (39). The study's objectives included segmentation and estimating the amount of blood involved in cerebral hemorrhage. A radiologist had labeled 27 CT pictures of a patient who had suffered an intracranial hemorrhage. The acquired CT data for the skull measured five millimeters thick, with 512 × 512 pixels making up each picture. It explained how to use Dynamic Graph CNN architecture for volumetric medical image analysis. Multiple EdgeConv layers were used to extract features, and pooling layers were used to acquire global features for jobs including both segmentation and classification. Using this architecture to segment and forecast bleeding in CT images was the objective of the project. The highest sensitivity bleeding segmentation was 98%. A DL-based model for the accurate detection of TBI was developed in a study (40). The data was gathered from 226 subjects which included 175 TBI patients and 51 normal individuals. Demographics showed differences in age and gender mostly in middle-aged and male groups. CT images of 512x512 pixels are cropped to 224x224 pixels, with 30 slices per image. Data augmentation doubled the images to prevent over fitting. Five-fold cross-validation method was used to split the data into training, validation, and test sets, totaling 1574, 197, and 197 images, respectively. The paper combined a ResNet-based CNN with a Squeeze and Excitation module, and RNN using LSTM. Ablation experiments were conducted on four network architectures (ResNet18, SENet, ResNet18+LSTM, SENet+LSTM) using the proposed dataset. Transfer learning improved accuracy and convergence speed. SENet+LSTM achieved the accuracy of 95.9% which was the highest among other models, with 93.3% sensitivity and 98.9% specificity. The lower sensitivity might have been due to the larger amount of injury data during training, leading to more learned positive features. A unique automatic method for segmenting the bleeding subtypes on a Computed Tomography scan, using an integrated CT scan with a bone window as input for a deep learning network, was suggested in a study (41). The classes were non-hemorrhage, Subdural Haemorrhage (SDH), Epidural Hemorrhage (EDH), Intraparenchymal Haemorrhage (IPH), combination of SDH and EDH, combination of SDH and IPH, combination of EDH and IPH and combination of the three hemorrhage subtypes. A 3D- CNN called Deep Medic was used. The input was a 2-channel voxel using CT scan subdural and bone window settings. To enhance the outcomes, post-processing methods including region-growing and size-based filtering are used. It achieved moderate DSCs at the slice level, with the highest for EDH (0.71). Patient-case DSCs were slightly lower. Comparisons between different CT scan settings showed similar results, with notably higher specificity when both windows were used. Applying post-processing improved results, maintaining comparable DSCs and sensitivities while enhancing specificity for SDH in the combined window setting. The segmentation method demonstrated improved performance compared to previous studies, achieving higher Dice similarity coefficients. Research was conducted to compare the performance of a DL model in radiology and in emergency medicine with neurosurgery residents in detecting and localizing intracranial hemorrhage resulting from TBI (42). A deep learning model was used for segmenting intracranial hemorrhages, including subdural hematoma, epidural hematoma, and intraparenchymal hemorrhage from non-contrast head Computed Tomography scans. The model generates segmentation results for different forms of hemorrhage based using input from subdural and bone windows on a two-channel voxel. With an overall accuracy of 0.89, the deep learning model outperformed residents in terms of sensitivity (0.82) but lagged significantly behind in terms of specificity (0.90). When it came to identifying SDH, the deep learning model was the most accurate (sensitivity = 0.85). The model demonstrated superior sensitivity in ICH detection in various subtypes compared to the average performance of the residents. Important clinical characteristics linked to the risk of TBI in very young children, a challenging population to assess due to limited verbal ability and developmental factors, were identified in a study (43). The PermFIT framework was employed, and the study included 42,412 participants, with 10,718 children (under the age of two years). The analysis focused on 1,429 children under two years with completed Computed Tomography scans and no missing values for the 24 clinical features. Various models, including random forest, support vector machine, deep neural network, and XGBoost were compared. Among these, the DNN model demonstrated superiority. It identified 9 significant features and performed better than other methods with accuracy of 0.915, AUC 0.794, and precision-recall area under the curve as 0.974. Associations between CT markers of diffused intracranial injury and high-frequency physiology in TBI patients were explored in a study (44). Utilizing the HR ICU sub-study cohort of CENTER-TBI, including 11 patients, they examined Twenty-Five Computed Tomography lesion variables in comparison with high-frequency physiology parameters. The logistic regression model analysis revealed a connection between deep peri-contusional edema and impaired cerebrovascular reactivity, as assessed by mean pressure reactivity index (PRx) above the defined thresholds. The study utilized arterial blood pressure measurements and employed a altered version of Deep Medic, a 3D CNN, for CT image processing, demonstrating consistent correlations between diffuse IC injury patterns and compromised cerebrovascular reactivity. Table 2 lists the findings of these works.

Table 2: Deep Neural Networks for TBI Detection with CT Scan Images

Authors	Data Used	Architecture	Technique	Results
Ellethy *et al., (*23)	15,271	-Random Forest feature selector with shallow ANN having three layers -a deep ANN with five layers, including three hidden layers with rectified linear unit neurons	ANN	ANN works well in identifying existence of mTBI in children
Hale *et al.,* (24)	14,969	-Instance hardness threshold algorithm using 5-fold cross-validation -DANN	ANN	Constructed a highly sensitive tool to diagnose CRTBIs
Wang *et al.,* (25)	1301 TBI patients at West China Hospital	-3-layer multilayer perceptron ANN model -Back-propagation learning algorithm included with 5-fold cross-validation.	ANN	ANN prediction model had a higher accuracy compared to nomogram model
Ellethy *et al.,* (26)	14,983 scans of < 18 years	-DANN model with clinical features of the PECARN rules -Instance hardness threshold algorithm using Five-fold cross-validation	ANN	DANN model replicates the PECARN rule, showing similar sensitivity and better specificity in predicting pediatric CT need for mild TBI than the original rule.
Adil *et al.,* (27)	-TBI patients a tKampala, Uganda, from 2016 to 2020 -13 clinical variables as predictors -2164 patients used for model training	-DNN -Elastic-net regularized logistic regression -Shallow neural network	DNN, SNN and LRNet	SNN performed best

Miguel *et al.,* (28)	CENTER-TBI dataset 1: 98 scans 2: 839 scans	-segment a fresh dataset of scans automatically -correct manually -dataset of images to train the final CNN for multiclass, voxel-wise lesion type segmentation	CNN	-CNN-derived lesion volumes - mean difference of ● 0·86 mL for intraparenchymal hemorrhage ● 1·83 mL for extra-axial hemorrhage ● 2·09 mL for perilesional oedema ● 0·07 mL for intraventricular hemorrhage.
Phaphuangwittayakult *et al.,* (29)	public datasets: 1: RSNA 2019 Brain Hemorrhage Challenge (755948 scans) 2: PhysioNet (2814 scans) private dataset: 3: CMU-TBI (19946 scans)	DeepMedic and EfficientNet. 11 NN layers, optimized DeepMedic model for multi-class segmentation on CT scans	CNN	**-Accuracy:** ● 98.62% CMU-TBI dataset ● 96.54% SDH classification ● 96.21% for all hemorrhage subtypes(average) ● -outperformed U-Net and UNet++
Gautam *et al.,* (30)	HIMS 1: Ischemic images 2:Hemorrhagic stroke images	Image fusion for better classification results	CNN	-Accuracy: ● Dataset 1: ● Experiment 1- 98.33% ● Experiment 2- 98.77%, ● Dataset 2: ● Experiment 1- 92.22% ● Experiment 2 - 93.33% -proposed CNN model performed better than AlexNet and ResNet50
Remedios *et al.,* (31)	-NIH and Vanderbilt University Medical Center -27 scans by CNRM and NIH, 18 scans in de-	-2D Inception Net-based model with ReLU activation and modified Inception Module. -Secure server-based framework for private data access, allowing	CNN	-average Dice similarity coefficient of 0.64

	identified form	model training without sharing datasets		
Zhang *et al.,* (32)	636 images	-VGG-SE-PCR neural network for computer-aided diagnosis of TBI integrated with VGG-S and a module that retains association between pixels	CNN	**-Accuracy:** 89.3% -better performance in terms of diagnostic accuracy when as opposed to alternative state-of-the-art methods
Rosnati *et al.,* (33)	Routinely-acquired hospital admission CT scans	cutting-edge deep learning Segmenting TBI lesions to identify imaging biomarkers	CNN	-automatically extracted quantitative CT features showed comparable/superior predictive capabilities compared to Marshall score
Pease *et al* (34)	537	-Transfer learning - for all trainable layers (excluding the final fully connected layer (FC8)) -Holistic prediction of long-term outcomes after severe TBI by combining information from CT scans and clinical data.	CNN	-fusion model maintained its predictive power for mortality (AUC 0.85) -showed a lower performance for predicting unfavorable outcomes
Wang *et al.,* (35)	25,272	SE-Resnext101, Densenet169, and Densenet121— utilized for CNN classifier	CNN	-Highest detection accuracy - IVH (Area Under Curve: 0.996, specificity: 0.974, sensitivity: 0.975) -Lowest for SDH (AUC: 0.983, specificity: 0.932, sensitivity: 0.946).
Mansour *et al.,* (36)	82 of <= 72 years	-KT-EHO algorithm was applied to indicate the diseased portions - Adagrad (AG) optimizer optimized Inception v4 for classification and identification	CNN	Precision: 95.26% Accuracy: 95.06% DL-ICH model outperformed WA-ANN, SVM, U-Net, WEM-DCNN, ResNexT

Mushtaq *et al.,* (37)	200	-Adagrad (AG) optimizer optimized Inception v4 for classification and identification. -Max-pooling, global average pooling, dense, and convolutional 2D layers make up BHCNet.	CNN	**Accuracy** : 95% after 24 epochs, **Precision**: 90.90% **Sensitivity**: 100% **Specificity**: 90% **F1-score**: 95.23%.
Jain *et al.,* (38)	5000+	U-Net–based CNN	CNN	-Icobrain(utilizing a U-Net–based CNN) is a reliable tool for quantifying CT features in acute TBI cases
Irene *et al.,* (39)	-27 head Computed Tomography scans (from the Cipto Mangunkusumo National General Hospital)	-Dynamic Graph CNN -Multiple EdgeConv layers	CNN	Sensitivity: 97.8% Specificity: 95.6% Absolute percentage error: 99.95
Chao *et al.,*(40)	226 (175 TBI patients and 51 normal individuals)	-ResNet-based CNN with a Squeeze and Excitation module -RNN using LSTM.	CNN RNN	-SENet+LSTM - highest Accuracy: 95.9% Sensitivity: 93.3%, Specificity: 98.9% -Our TBI dataset is positively impacted by the SE module and LSTM.
Inkeaw *et al.,* (41)	CT scans 1.5 mm slide thickness	-DeepMedic	CNN	-The median sensitivities with IQR for SDH, EDH, and IPH were 0.58 (0.57), 0.64 (0.72), and 0.35 (0.77), respectively, and for ICH they were 0.70 (0.51). -Median specificity: higher than 0.99
Angkurawaranon *et al.,* (42)	- There were 300 head CT investigations in all -166 of them	-Model can segment EDH, SDH, and IPH on a Computed Tomography scan (a variant of the DeepMedic model)	CNN	-DL model - most sensitive in detecting SDH with a sensitivity of 0.85 -Accuracy: 0.89

	fell into the ICH group -134 of them fell into the non-ICH group.	-Has four parallel channels to handle the input at various resolutions.		-Sensitivity: 0.82 -Specificity: 0.90
Zou *et al., (*43)	-42,412 participants 10,718 children under 2 years. -Analysis focused on 1,429 children with completed CT scans and no missing values for the 24 clinical features	-PermFIT framework was employed -logistic regression model is used	PermFIT-DNN	-Accuracy: 0.915 AUC: 0.794 PR-AUC: 0.974 -The DNN model was the most effective framework, outperforming other techniques including RF, XGB, and SVM.i.e RF, XGB, and SVM
Zeiler *et Al.*, (44)	165 patients - CENTER-TBI HR ICU	25 CT lesion variables	PermFIT-DNN	-Significantly enhanced PRx at threshold 0 was seen in patients with an age mean of 51.4 vs. 41.4 years, a higher Rotterdam Computed Tomography score, a bigger extra-axial hematoma volume (31.0 vs. 13.3 cm^3), and a higher cortical contusion edema volume (8.3 vs. 4.4 cm^3). -The only CT characteristic that was shown to be substantially correlated with higher percentage time and hourly dosage beyond the PRx threshold was sternal compression ($p < 0.002$).

Diagnosis Using MRI Images

The complex nature of Traumatic Brain Injury requires accurate diagnostic tools to ensure optimal patient care. MRI helps to study the brain structure and its functions for a patient suffering with TBI. Recently, the medical field has seen a revolutionary shift with the incorporation of deep learning methods which have offered wonderful opportunities in analyzing complex MRI data for predictive models. This section explores the current state of deep learning applications in predicting TBI using MRI scans and briefs these works in Table 3.

MLP

Data from a nationwide study in Taiwan on traumatic brain injuries (TBI) were utilized to determine the need for open-skull surgery (45). The dataset consisted of 12,640 cases, with 75% randomly chosen for training and 25% for testing. The initial model employed was a multi-layer perceptron (MLP) neural network including an input layer (consisting of Eleven nodes), a hidden layer (comprising 7 nodes), and a single node output layer. Another model was an RBF neural network consisting of a lone hidden layer. Both neural network models consistently outperformed a logistic regression model, with the MLP achieving an ROC area of 0.897 and the RBF network achieving 0.880. This suggests the effectiveness of MLP and RBF neural networks in predicting the need for open-skull surgery in TBI patients.

CNN

Convolutional Neural Network is mainly used for processing and analyzing visual data. It comprises three layers called convolutional, pooling and a fully connected layer. CNNs can analyze medical images such as CT scans and MRIs which are commonly used to diagnose and evaluate the severity of TBI. Further we can also extract relevant features from these medical images aiding in the detection and classification of TBI as well as assess the severity and location of injuries. They can be used to predict the potential outcomes and recovery trajectories of individuals with TBI. This information can assist healthcare providers in making more practical decisions about treatment and rehabilitation. Several studies have successfully introduced CNN models designed for segmenting lesions and contusions within MR images of the brain in TBI patients. A CNN model, employing a unique architecture known as Inception, developed by Google, was presented in a comparative study (46). A three layer Inception network was used to segment lesions from multi-contrast MR images. The model showed better accuracy results on the images of 18 TBI patients when contrasted with two other TBI lesion segmentation methods, one developed on the basis of Deep Medic and the other developed on random forests. The network utilized a series of cascading modules, each of which was a modification of the Inception module. They introduced a modification by adding an additional pathway with an average pooling layer followed by 3×3 convolutions. The addition of average pooling offered a lower-resolution feature map without down sampling the image, which has practical implications elaborated upon later. On average, the RF algorithm tended to produce under-segmentation, while Deep Medic tended to over-segment and generate more false positives. The above study used the Deep Medic model for successful segmentation of lesions in the brain of patients suffering from Traumatic Brain Injury. The Deep Medic model was utilized to implement CNNs for predicting fiber tract masks in a study (47). Each of the 12 fiber tracts was individually trained using a separate Convolutional Neural Network (CNN). Deep Medic addressed class imbalances by segmenting images for training and ensuring an undivided focus on background and foreground voxels. This adaptation was automatic, helping to improve model performance in situations with varying class distributions. Deep Medic initialized its network weights using a normal distribution, employed a Parametric Rectified Linear Unit nonlinearity for input units, utilized a cross-entropy loss function that simultaneously evaluates predictions across multiple voxels, and optimized the network weighted units through stochastic gradient descent. A deep learning method utilizing a Siamese Network to acquire a distinct feature representing classification of individual-subject ICA components was introduced in a study (48). Siamese Networks represent a distinct form of deep learning architecture consisting of a minimum of two identical neural networks called encoders. Their parallel structure enabled the model to grasp similarity relationships, which can replace direct classification. During inference, the network took sets of images (usually two or more) and calculated the distance between them. The distance computed was learned from the training data, which specifies small distances for images from the same category (RSN) and large distances for images from different categories. A deep learning framework for extracting intracranial tissues from MR images in mild or severe TBI cases was developed in a study (49). They employed a CNN framework that was tested on a dataset comprising 19 human patients with varying TBI severity, 16 normal mice, and 10 mice with repeated TBI. Evaluation against three brain extraction techniques showed significant accuracy improvement in both human and rodent images, highlighting the method's versatility and effectiveness. Dynamic functional connectivity (dFC) was investigated to analyze the impact of traumatic brain injury on large-scale neuronal networks in a study (50). The study included healthy controls and participants with mild to severe TBI. Functional MRI data were collected during a cognitive task, and preprocessing involved steps like repairing bad slices, slice time correction, realignment, and despiking. Independent component analysis (ICA) was used for brain parcellation, resulting in 44 components for both static and dynamic connectivity. The study revealed that the probable frequency of entering a specific state during Run 1 predicted the frequency during Run 2 for both TBI and healthy controls. However, the TBI group showed fewer state transitions, indicating reduced network dynamics compared to healthy controls.

Other Variants of CNN

An algorithm called MU-Net-R, which uses an ensemble of U-Net-like CNNs to automatically segment the hippocampus of normal and injured rats, was developed in a study (51). The CNN featured an encoder/decoder structure with skip connections, and pooling and unpooling operations for effective feature mapping at different resolutions. Each block in the architecture included three iterations of ReLU activation, convolution, and batch normalization, contributing to the precision of the segmentation strategy. They made different choices for filter dimensions based on each dataset and for segmenting images with anisotropic voxel sizes, 2D convolutions were preferred. Unlike MU-Net, which consistently utilizes 64-channel convolutions and 5x5 filter sizes, their design varies the number of convolution operations and filter sizes. These changes resulted in a significant reduction in the total number of parameters, going from 2,087,944 (for 2D) and 10,286,344 (for 3D) in the case of MU-Net, down to 428,436 and 1,125,716, respectively in their model. This approach allowed them to achieve equivalent segmentation quality to MU-Net while employing fewer parameters. A comprehensive study focusing on the detection of cerebral micro bleeds (CMBs) as biomarkers for traumatic axonal injury (TAI) in traumatic brain injury (TBI) cases was conducted in a study (52). They developed a classification model called Patch-CNN and two segmentation approaches (Segmentation-CNN and U-Net) for CMB detection. The 3D-FRST (Fast Radial Symmetry Transform) was employed for initial CMB candidate detection. Traumatic CMBs can have varying shapes, so careful consideration was given to hyper parameter selection for 3D-FRST. Identified points of interest by 3D-FRST served as central points for creating 3D patches (21x21x21 dimensions). These patches were used to train the Patch-CNN model to distinguish true lesions from false positives. The Segmentation-CNN model shared the same architecture as the Patch-CNN model, including the kernel sizes, the feature volumes of the filters, and the number of convolutional layers. The sole architectural difference lies in the exclusion of the dropout layer. This decision was based on the understanding that the dropout layer wasn't essential for enhancing generalization in segmentation tasks. The primary contrast between these models was the dimensions of their input as well as output layers, which consequently affected the size of transitional layers. The U-Net model was based on the 3D-Unet model. The original model was initially created for wide scale volume segmentation tasks. In contrast, their specific objective was to segment small structures, such as Cerebral Micro bleeds (CMBs). To align the network with their task, they made several adjustments. In terms of network structure, they made a few changes compared to the original model. Their model featured two pooling layers instead of three. Additionally, they introduced an intermediate layer with a 1x1x1 kernel into their skip connections. These modifications helped in enhancing the activation energies between the encoder and decoder layers to ensure that the network is suitable for their specific task. Three dimensional Convolutional Neural Networks (3D-CNN) plays an important role in the development of prediction models for TBI. The utilization of advanced deep learning architectures enables these models to recognize certain subtle alterations which indicate traumatic brain injuries. Leveraging volumetric data, 3D-CNNs exhibit heightened sensitivity in detecting traumatic lesions, enabling precise localization and characterization. The integration of 3D-CNNs in the predictive modeling of Traumatic Brain Injury delineates their role as sophisticated tools at the confluence of artificial intelligence and medical imaging, promising advancements in diagnostic precision and, consequently, improved clinical outcomes for individuals affected by traumatic brain pathologies. A Three-Dimensional CNN for brain lesion segmentation was proposed in a comprehensive study (53). Their lesion segmentation method comprised two main components, a 3D CNN that was responsible for producing extremely accurate segmentation maps and a 3D CRF (Conditional Random Field) that enforced regularized constraints on CNN outputs in order to produce hard segmentation labels. Furthermore, they explored the development of deeper 3D CNNs, which can provide greater discrimination. Their design incorporated a dual pathway architecture that concurrently processed multiple-scaled input images. They integrated a fully connected 3D CRF which eliminates false positives effectively.

Other Deep Learning Models

Conventional Deep Learning models play a pivotal role in the prediction of TBI by leveraging intricate patterns within medical imaging data, such as MRI scans. By training on diverse datasets, these models can discern subtle abnormalities indicative of TBI. The integration of these models in TBI prediction not only enhances diagnostic accuracy but also contributes to the ongoing effort to establish non-invasive, efficient tools for early detection and prognosis in the clinical management of traumatic brain pathologies. An illustrative instance was found in some experiments where a deep learning model based on a CNN with residual learning architecture was assessed (54). This model was specifically designed for the prediction of Traumatic Brain Injury (TBI) severity utilizing information extracted from magnetic resonance (MR) images. When tested with different subjects of varying TBI levels, the model achieved greater accuracy and sensitivity results as compared to others. This process entailed expanding the image dataset through a variety of transformations that maintain the original labels. These transformations resulted in multiple distinct versions of the original images, achieved through techniques such as gamma correction, translation, rotation, random noise injection, scaling, and random affine transformations. The residual learning model utilized ResNet-50 CNN architecture. The ResNet architecture tackles the disappearing gradient issue in deep Convolutional Neural Networks by incorporating connections that create direct links from shallow to deeper layers. These connections allow the network to understand residual information, acting as a form of boosting. Here a basic building block is expressed as $y = F(x, Wi) + x$; here x and y represent input and output vectors, and F is the residual mapping. Matching dimensions between x and F is crucial, and a linear projection Ws may be applied through a shortcut connection if needed: $y = F(x, Wi) + Wsx$. Transfer learning is employed by fine-tuning a pre-trained ResNet-50 on a large dataset and then adapting it to the smaller Traumatic Brain Injury (TBI) MRI data. The weights of ResNet-50 layers remain fixed, and only the fine-tuning layers are trained with randomly initialized weights, leveraging knowledge from the pre-trained model for improved learning. In a comprehensive study, an auto encoder was introduced to observe changes in the spatial properties of structural and functional brain networks in children who experienced Traumatic Brain Injury (55). The structural MRI data of each individual underwent preprocessing steps, including motion correction, removal of non-cerebral voxels, and intensity normalization. Addressing head motion was crucial, as significant movement could impact imaging data quality and lead to inaccurate tractography results. Instances of substantial head movement were defined and resulted in the exclusion of specific subjects from the study. The research aimed to explore the model's capability to predict post-TBI attention deficits. A two-stage framework was proposed for efficient and accurate detection of cerebral micro bleeds (CMBs) in medical imaging by a comprehensive study (56). The first stage utilized a 3D FRST on composite Susceptibility Weighted images for candidate detection. The second stage involved a deep neural network trained on 154 datasets and tested on 41 cases. The model achieved a 95.8% sensitivity rate, 70.9% precision, and 1.6 false positives per case. Trained on a dataset comprising 220 cases from various studies, the model demonstrated performance comparable to experienced human raters and ousted other recent CMB detection methods. Another comprehensive study on traumatic brain injuries (TBI) aimed to address the rising incidence of TBI globally, with a minimum of 50 million cases of TBI occurring annually (57). Patients with severe TBI often face grim prognostic outcomes, leading to physical disabilities and joblessness. Traditional therapeutic options, including surgical procedures, medicines, and exercises, have reduced capabilities due to complications such as hypoxia, ischemia, poor nutritional status, and inflammatory reactions in the traumatic area. The results indicated positive effects on neurological functions, evidenced by electrophysiological changes, MRI scans, and behavioral assessments. The motion capture system provided a precise analysis of gait characteristics, revealing improvements in locomotory abilities. The research provided valuable insights for treating traumatic brain injuries. A residual Fully Convolutional Neural Network (FCNN) incorporating an attention-guided refinement unit was proposed to enhance the accuracy of amygdala and sub nuclei segmentation in brain images (58). The dual branch design and the top-down attention mechanism improved feature fusion, outperforming original models and a multi atlas approach. The model demonstrated robustness to real-world variability in imaging conditions, showcasing generalizability to a challenging TBI dataset from various sites. The findings emphasized the model's potential for precise and generalized brain image segmentation, contributing to advancements in medical image analysis. The challenge of predicting TBI outcomes using diffusion tensor imaging (DTI) was addressed in an illustrative study (59). They developed a classification pipeline which included a deep learning framework along with statistical and periodic permutation tests. A deep learning multi-modal network independently trained models for each DTI measure (FA, MD, MO, and AD). Results were iteratively improved through Tract-Based Spatial Statistics (TBSS) permutation tests, using the MICCAI Challenge dataset of 27 subjects with three distinct categories: healthy individuals, group I patients, and group II patients. The proposed methodology showed potential for unbiased treatment of mild TBI and provided prognostic insights, assessing mTBI severity solely through DTI neuro-images. A segmentation model for cerebral microbleeds and non-hemorrhage iron deposits was developed using a distributed sample of 24 individuals from the MESA cohort (60). They modified the U-Net model with additional resolution layers for improved lesion detection. The multimodal approach, particularly utilizing QSM, showed promising results. In CMB detection, sensitivity and precision ranged from 0.84 to 0.88 and 0.40 to 0.59, respectively. For non-hemorrhage iron deposits, precision and sensitivity ranged from 0.62 to 0.75 and 0.75 to 0.81. The research demonstrates the importance of deep learning in automating the detection of small vessel disease lesions, making it suitable for extensive research studies.

Table 3: Deep Neural Networks for TBI Detection with MR Images

Authors	Dataset	Architecture	Technique	Results
Roy *et al.,* (46)	MPRAGE, T2-w, and FLAIR images of 18 patients.	The design included three modified Inception modules, each comprising parallel layers of convolutions, max-pooling, and average pooling. Each module featured four pathways: one max-pooling layer and three convolutional layers of dimensions 1x1.	CNN	This method showed greater segmentation accuracy on all the 18 MRI images of TBI patients when compared with the other methods such as Random Forest and a CNN based Deepmedic Algorithm.
Pomiecko *et al.,* (47)	240 subjects including	The CNN architecture comprised one input layer,	CNN	The median Dice scores for control and

	controls and TBI patients.	two groups of 10 convolutional layers, one classification layer and two fully connected layers.		TBI subjects using CNN were 0.70 and 0.73 respectively. This architecture was used by networks for predicting white matter masks.
Chou *et al.,* (48)	Data was grouped into four sets to train the model and included 179, 10, 198 and 21 healthy subjects respectively	-A minimum of two parallel neural networks called Encoders (had an input layer) -two fully connected ReLU layers -output layer.	CNN	Outperformed traditional CNN and other methods with an accuracy rate of almost 100% on a holdout data set
Roy *et al.,* (49)	The first dataset consisted of 19 TBI patients. The second dataset included 16 normal mice and the third cluster contained 10 mice used in a repetitive TBI model.	The Inception block contained parallel pathways to 3^3 and 5^3 convolution filters and max pooling, preceded by 1^3 convolutions. There was further concatenation of 3^3 average pooling layers and 3^3 convolutions in the architecture.	CNN	-Involved experiments on human as well as mouse MR images -showed greater accuracy in skull stripping -It showed better stripping masks for all the three sets of subjects.
Gilbert *et al.,* (50)	The dataset included 23 TBI patients and 19 healthy adults.	A functional connectivity network was developed for each subject using independent component analysis (ICA) for brain parcellation.	CNN	High reproducibility (r-value > 0.8) was observed in the cumulative frequency of dynamic network states across both samples.
Feo *et al.,* (51)	-Adult male Sprague Dawley rats - testing subjects. -56 rats (out of which 43 were suffering from TBI)	A bottleneck layer linked both the decoder as well as encoder branches. Each block comprised three iterations of batch normalization, ReLU activation and convolution.	MU-Net-R Algorithm	The model was able to achieve Dice scores above 0.90 using the MU-Net-R algorithm.

Koschmieder *et al.*, (52)	The dataset included brain MR images of 45 patients with moderate to severe TBI.	Patch-CNN being fully convolutional had candidates being used as core points for 3D Patches of dimensions 21x21x21. The Segmentation-CNN had a similar architecture as Patch CNN but the dropout layer was removed. The U-Net model had two pooling and upsampling layers along with an intermediate layer.	CNN	The U-Net being the best model, achieved a 90% detection rate with false positive counts of 17.1 in patients suffering from TBI and 3.4 for healthy patients. The Patch-CNN model with a sensitivity rate of 90% produced 20.6 false positives in patients affected by TBI and 6.9 false positives in healthy patients. The Segmentation CNN model achieved a sensitivity rate of 90% with false positive counts of 19.2 for TBI patients and 5.5 for healthy patients.
Kamnitsas *et al.*, (53)	The dataset included 66 patients with moderate to severe TBI.	A 3D CNN model comprising 11 layers and a dual pathway.	3D CNN	The proposed model was not only computationally efficient but also solved the segmentation problems.
Yeboah *et al.*, (54)	203 TBI patients from 18 to 79 years old.	A 5 stage model, each equipped with a convolutional as well as an identity block. The convolutional block is made up of 3 stacked layers.	ResNet-50 CNN architecture	The model demonstrated high sensitivity and specificity when tested on subjects with varying degrees of TBI severity.
Cao *et al.*, (55)	110 subjects including 55 subjects as TBI patients and the other half as group-matched controls.	The framework included three basic components: an encoder, a decoder and a classifier. The encoder and the decoder consisted of a hidden layer, an input layer and an output layer while the classifier only had an output layer and a single hidden layer.	Deep Learning framework	The model had an accuracy rate of 82.86% and was able to distinguish people suffering from TBI and controls.
Liu *et al.*, (56)	This study comprised 220	A two stage framework for detecting cerebral	Deep Learning	The model had a 95.8% sensitivity rate, 70.9%

	datasets having 100 cases of hemodialysis, 97 cases of TBI, 13 cases of stroke, and 10 healthy controls.	microbleeds (CMB) including a FP reduction stage leveraging deep neural networks.	framework	precision rate, and 1.6 FPs per case.
Jiang *et al.,* (57)	The research study used 24 canines as subjects and they were further distributed into four groups randomly.	-fabricating a scaffold using silk fibroin and collagen -implant them with hUCMSCs at the brain trauma sites.	Deep Learning framework	Implementing this advanced therapy for traumatic brain injury involves repairing the structure and promoting functional recovery.
Liu *et al.,* (58)	MRI images of 14 individuals with an average age of 28.9 years.	FCNN architecture (uses encoder-decoder structure)	Deep Learning framework	The model achieved better performance compared to other segmentation methods as it was able to segment data within seconds.
Cai *et al.,* (59)	27 subjects were included in the research which were then further categorized into Group I patients, Group II patients, and healthy patients.	The architecture consisted of 2 components: a dimension reduction layer and a consolidation layer for integrating outcomes from all metrics.	Deep Learning framework	This multi-modal deep learning approach was quite flexible to be able to predict TBI accurately.
Rashid *et al.,* (60)	The model used 24 individuals as a dataset to segment the lesions.	Six resolution layers were used by the DEEPMIR model to detect small lesions like CMB.	Quantitative susceptibility mapping	The results proved that deep learning could even detect small lesions particularly CMBs and non-hemorrhage iron deposits.

Diagnosis Using Other Data

In addition to EEG, CT and MRI, there are numerous other types of input data, used for the classification of TBI. These include wide field imaging which records neural activity in the form of calcium signals, using kinematics (trajectory, velocity, acceleration of movements etc.) as input, involving existing datasets, using blood oxygen level-dependent functional magnetic resonance imaging (BOLD-fMRI), acquiring images via bright-field microscopy, using HD-sEMG recordings, utilizing audio recordings from existing datasets, analyzing speech patterns. The diversity in these input techniques brings in development of innovative approaches for the classification and comprehensive understanding of Traumatic Brain Injuries (TBI)'s impact, accurate diagnostics and treatment, as briefed in Table 4.

MLP

Data from a nationwide study in Taiwan on traumatic brain injuries (TBI) was utilized to determine the need for open-skull surgery (45). The dataset consisted of 12,640 cases, with 75% randomly chosen for training and 25% for validating. Initially a multi-layer perceptron (MLP) neural network featuring an eleven-node input layer, a hidden layer with 7 nodes, and a single-node output layer using a sigmoid transfer function was employed. Another model was an RBF neural network with a single hidden layer. Both neural network models consistently outperformed a logistic regression model, with the MLP achieving an ROC area of 0.897 and the RBF network achieving 0.880. This suggests the effectiveness of MLP and RBF neural networks in predicting the need for open-skull surgery in TBI patients. Traumatic brain injuries and intracranial hemorrhages (ICH) were investigated with a deep learning-based classification model (61). The DL-ICH model integrated Inception v4 for extracting features and a MLP for classification. Through tenfold cross-validation, the DL-ICH model exhibited high sensitivity (93.56%), specificity (95.56%), precision (95.26%), and accuracy (95.06%). Comparative analysis with existing models highlighted the DL-ICH model's superiority in terms of specificity and sensitivity, emphasizing its potential for accurate and timely ICH diagnosis. The prediction of neurocognitive rehabilitation outcomes in acquired brain injury (ABI) patients using data mining was focused on in a comprehensive study (62). Data from the PREVIRNEC platform was used to build three predictive models: MLP, decision tree, and general regression neural network. The dataset included 10191 task executions related to memory cognitive function from 250 patients with mild to severe cognitive impairment. Decision tree demonstrated superior results with 90.38% accuracy rate, outperforming MLP (78.7%) and GRNN (75.96%). The study highlights the potential of decision tree algorithms in predicting cognitive rehabilitation outcomes for TBI patients. The validation of Artificial Neural Network models for predicting in-hospital mortality in TBI surgery, comparing their performance with logistic regression models were proposed in a study (63). Exclusion criteria filtered multiple TBI procedures, cerebrovascular diseases, incomplete data, and patients under 18. The ANN architecture had a standard feed-forward, back propagation structure with three layers. Results showed that ANN models outperformed logistic regression, demonstrating Hosmer-Lemeshow C statistic (43.90 vs. 53.18), superior accuracy (95.23% vs. 82.44%) and AUC (89.61% vs. 77.39%). Sensitivity analysis highlighted key predictors for in-hospital mortality. The study concluded that ANN models exhibited superior performance in various metrics compared to logistic regression, emphasizing their potential for predicting TBI surgery outcomes. The application of artificial neural networks (ANNs) for predicting survival outcomes in TBI cases was explored in a study (64). The dataset, drawn from the National Trauma Data Bank (NTDB), included over 200,000 records from 712 hospitals, focusing on head trauma cases with positive head CT scans. The ANN architecture, featuring interconnected nodes in multiple layers, was designed to capture nonlinear interactions among input variables. The training process involved a unique "informative sampling" technique in a feed forward 3-layer neural network, with thirty ANNs trained simultaneously, and predictions averaged for enhanced accuracy. Logistic regression models were developed for comparison, and a testing set comprising 100 novel patients was created for evaluation. Results demonstrated that ANNs consistently outperformed both neurosurgeon clinicians and logistic regression models in terms of sensitivity, discrimination and accuracy. This highlighted the potential of ANNs as effective predictive modeling tools in neurosurgery, although the study acknowledged limitations related to dataset variability and the absence of key variables, emphasizing the need for more detailed databases for future refinement. While the above papers focused on in-hospital mortality, data mining techniques were integrated with serial GCS scores and clinical parameters to predict 6-

month functional outcomes and mortality in patients with TBI (65). The retrospective analysis included data from 115 adult patients with moderate-to-severe TBI presenting at a trauma center. The input dataset included serial GCS measurements at the emergency department, 7th day, and 14th day, along with relevant laboratory data. Four predictive models (artificial neural network - ANN, naïve Bayes - NB, decision tree - DT, and logistic regression - LR) were utilized to forecast outcomes. The ANN model demonstrated the highest accuracy (96.13%) in predicting favorable functional outcomes, while the NB model excelled in mortality prediction (AUC of 90.14%). The study underscored the importance of serial GCS measurements, particularly on the 7th and 14th days, in predicting outcomes. Key attributes influencing predictions included GCS scores at different time points and age. The ANN model, with its superior performance, was suggested as optimal for functional outcome prediction, while the NB model was deemed most effective for mortality prediction. The performance of ANN, multiple regression, and classification and regression trees in predicting outcomes for 1644 patients in the TBI Model Systems database one year post-injury was compared in a study (66). Patients' Functional Independence Measure (FIM), Disability Rating Scale (DRS), and Community Integration Questionnaire (CIQ) were recorded. The ANN consisted of three main layers—input, hidden, and output—allowing for the collective impact of multiple independent variables on the output layer. The results suggested a potential bias in the sample toward follow-up, with 53.5% of patients meeting inclusion criteria for modeling procedures. Patients tended to experience higher rates of loss to follow-up when their admission FIM and DRS scores suggested less severe injuries, coupled with shorter stays in acute care. The need for an accurate traumatic brain injury (TBI) predictor through a deep learning approach, focusing on concussion classification utilizing reconstructed cases of injuries in the American National Football League (NFL), was addressed in a paper (67). The study employed the Worcester Head Injury Model to simulate reconstructed head impacts in the NFL, computing peak white matter fiber strains at each voxel. The deep learning architecture employed a network structure with 5 fully connected layers and ReLU activation, demonstrating superior performance in concussion prediction compared to support vector machine (SVM) and random forest (RF) classifiers. Deep learning achieved the highest cross-validation accuracy, sensitivity, AUC, and the lowest .632+ error, emphasizing its efficacy in TBI prediction.

CNN

A method to detect mild traumatic brain injury (mTBI) early by combining graph embedding features with 2D-CNN was suggested in a study (68). The Thy1-GCaMP6s transgenic mice utilized in this study consist of five males and females The primary input technique involved recording cortical activity to capture neural activity in the form of calcium signals (widefield imaging). Node embedding features were extracted from brain functional networks using the Node2vec algorithm, resulting in the construction of 40 images that were evaluated through a five-fold cross-validation method. The Convolutional Neural Network (CNN) consisting of 7 layers, started with an input layer. It included two convolutional layers: the first had 32 kernels of size 3x3 with ReLU activation, and the second employed 3x3 kernels with ReLU activation. Following this, a 2x2 max-pooling layer reduced the spatial dimensions. Subsequently, two fully connected layers with 32 and 16 nodes, respectively, were integrated, leading to an output layer with two nodes for classification using the softmax function. The learning rate for optimization was set at 0.001. 2D CNN achieved the highest accuracy of 95.8%. On the other hand, the graph node embedding method couldn't differentiate between normal and mTBI networks. In a similar work, early mTBI identification and its use in network measures through frequency-specific analysis in functional networks were focused on in a study (69). Before and after inducing injury, activity in the cortex of 15 injury and control Thy1-GCaMP6s mice each was recorded using white field calcium imaging. The high frequency band network's measurements resulted in higher classification accuracy in graphs, contrasting the lower classification accuracy of the low frequency band network. The CNN classifier model recorded an average classification accuracy of 97.28% which proved to be better than the 2D CNN used in the previous paper. In contrast to detecting or predicting early mTBI, convolutional neural networks were proposed to predict 14-day mortality in TBI patients, with CNN performance compared to conventional machine learning techniques in a study (70). Various optimization methods, including RMSProp, Adam, Adamax, and SGDM, were used in neural network simulations. Two CNN architectures, CNN1 and CNN2, were employed for mortality prediction. CNN1 had a parallel structure with three blocks, each containing Conv1D layers with different kernel sizes. CNN2 had a serial architecture with 1D convolutional layers, batch normalization, ReLU activation, dropout, and dense layers. The accuracies and area under the ROC, 0.859 and 0.911, were achieved with a multilayer perceptron network and CNN, indicating CNN's superiority over other machine learning algorithms in this context. While detection of mTBI is important, differentiation of mTBI from healthy conditions is also crucial. A method to differentiate mild traumatic brain injury (mTBI) from healthy conditions in Thyl-GCaMP6s transgenic mice using wide field optical imaging of cortical activity was focused on in a paper (71). Image representation was executed using a Bag of Visual Words (BoVw) technique. Two primary models, Vision Transformer (ViT) and Convolutional Neural Network (CNN), were explored.Twenty-by-twenty-by-one-pixel patches, twenty-five in number, were extracted from each of the 2047 images produced during every recording session, which consisted of eight trials. The three 2D convolution layers were present in both the encoder and decoder networks. Features extracted and word histograms were then fed into a SVM for classification for a 10-fold cross-validation. The conclusion suggested that CNNs were outperformed by ViT and BoVW models considering classification accuracy as the main parameter showcasing their potential for mTBI identification. Other than wide-field optical imaging, measured kinematics is also widely used to detect TBI. The global public health issue of mild TBI in contact sports was addressed (72). They aimed to develop a computational model for estimating detailed brain strains using measured kinematics as input. The CNN architecture with 32 filters of sizes 3x10, 1x10, and 1x5 demonstrated high accuracy (R^2 of 0.937, RMSE of 0.018). The model, tested on various impact datasets, consistently achieved high R^2 (0.884 - 0.915) and low RMSE (0.015 - 0.026). The CNN approach outperformed reduced-order models, showcasing its effectiveness in predicting regional brain strains for different impact scenarios, including high school football impacts. In their research proposal, the important role of efficient brain strain estimation for the repeated use of head injury models was emphasized, similar to the previous work (73). They utilized a dataset comprising head impact kinematics from two public databases, resulting in 2694 augmented impacts simulated using the anisotropic Worcester Head Injury Model (WHIM) V1.0. The creation of static images involved concatenating rotational velocity (vrot) and corresponding rotational acceleration (arot) profiles as inputs for each augmented impact in the CNN. Three training strategies were assessed: 1) "baseline" with random initial weights; 2) "transfer learning" with weight transfer from a previous CNN model trained on head impacts from contact sports; and 3) "combined training," which involved merging previous training data from contact sports for training purposes. The combined training strategy produced the most optimal results, with the CNN achieving an R2 coefficient of 0.932 and an RMSE of 0.031 for peak MPS. Motor intent in post-traumatic brain injury (TBI) patients was aimed to be decoded using high-density surface electromyography (HD-sEMG) recordings (74). The dataset included five male TBI patients (TBI_1 to TBI_5), aged 27 to 34 years. A fully connected convolutional neural network (FC-CNN) architecture was employed, consisting of an input layer (L1), two convolutional layers (C2 and C3), one fully connected layer (F4), and an output layer (O5). The FC-CNN processed the HD-sEMG recordings to extract motor-related information. Subject TBI_3 achieved the highest accuracy at 98.92%, surpassing other subjects. The study demonstrated the potential of FC-CNN in decoding motor intent from HD-sEMG recordings in post-TBI patients. To understand injury mechanisms, predict outcomes, guide treatment strategies, and develop preventive measures, brain injury modeling for TBI is considered very crucial. A study was conducted with the purpose of enhancing subject specificity and efficiency in brain injury modeling (75). They extended an instantaneous convolutional neural network brain model. This was based on the anisotropic WHIM

V1.0. The researchers randomly scaled the WHIM and paired it with augmented head impacts generated from actual data to generate training samples. The individualized CNN achieved 86.2% while they cross-validated for model responses and 92.1% when they independently tested the model in a generic way. Using 11 subject-specific models without the need for individual neuroimages, CNN remained accurate. This research underlined the potential applications of injury mitigation and head protective gear design, particularly for youths. Brain injury modeling and bug severity models for TBI both aim to predict and understand the impact of traumatic brain injuries. The functional hyper connectivity in the first year of recovery after moderate to severe traumatic brain injury was studied (76). They used BOLD-MRI for this study. The dataset included 14 individuals with TBI and 12 healthy controls, scanned at three time points over the first year, post-injury. The Glasgow Coma Scale assessed injury severity, and neuropsychological tests were conducted. Preprocessing included motion correction, normalization, and nuisance signal regression. The study identified hyper connected regions in the left frontal Default Mode Network and ventral parietal attention network at Time-2. Interestingly, increased connectivity at Time-3 was associated with more efficient organization. The analysis revealed specific connectivity patterns at different recovery time points, contributing to the understanding of functional changes after TBI. Besides prediction and detection, there are many studies performed to further study the details of TBI. For example, a classification system was targeted for developing to determine activated microglia after traumatic brain injuries; that would also provide advancement of the cellular responses due to TBI (77). The cells that live in the nervous system's parenchyma are referred to as microglia. When a TBI occurs, the primary role of microglia is to eliminate cellular and molecular waste and restore normal brain environment. The study utilized images of Iba1-stained microglia from two brain regions, employing pre-trained Resnet18, Resnet50, and Resnet101 models for image classification (120x120 pixels). The CNN3CL architecture included three convolutional layers with ReLU activation and max-pooling. This was followed by fully connected layers and a softmax output. Training results showed Resnet18 achieved the best accuracy (95.5-98.8%) and F1 score (0.96-0.99) with 120 epochs. CNNs proved effective in differentiating microglia morphology in control and neuro inflamed brains, highlighting their value in neuroinflammation research. Among the works related to traumatic brain injury, there is particularly notable research which was done on developing a facial expression recognition (FER) model. It was made to enhance human-robot interaction designed especially for patients of TBI so that more enhanced communication and assistive technologies for the said population may be availed (78). This paper aimed to improve social interaction and assistance of trainers and physiotherapists in their work with TBI patients using robots. The input dataset consisted of 924 videos of TBI patients engaged in cognitive, physio, and social rehabilitation activities. Approximately 140,000 frames were captured at 30 fps for the dataset. Along with a combination of pre-processing techniques, this paper also involved deep neural architecture consisting of CNN and LSTM. The CNN, fine-tuned with a pre-trained VGG16-CNN model, extracted facial features, and the LSTM exploited temporal relations based on the extracted features. A conclusion can be drawn from the experimental results indicating the successful development and validation of the TBI-FER model on the CK+ database achieving a high accuracy of 91% in identifying various facial expressions in TBI patients. The results suggest that the Pepper-FER model was significantly outperformed by the TBI-FER model on both TBI and CK databases. This paper signifies the use of a customized training model for meaningful interaction with TBI patients.

RNN and its Variants

A prognostic model was created to predict long-term outcomes in TBI patients, with the goal of enhancing clinical decision-making and patient management over time (79). The study collected data from TBI patients at 18 different academic level 1 trauma centers in the United States, using 110 clinical variables as input for the model along with a deep RNN model. The researchers used a modified recurrent unit called GRU-D to predict the GOSE at six months after injury. They interpreted the predictions made by the RNN model using Shapley Additive Explanation (SHAP). The RNN model achieved an AUROC of 0.86 (95%

CI 0.83-0.89) for binary outcomes, while the comparison model's AUC was 0.69 (95% CI 0.67-0.71). RNN model outperforms the existing IMPACT model in terms of performance metrics, including AUC, F1 score, and Kendall's correlation coefficient. Based on SHAP analysis, the important features contributing to outcome prediction include age, pupillary reactivity, motor score, vital signs, and lab measurements. This model was trained on both static and time series data. A Deep Neural Network system was proposed to enable noninvasive, speech-based assessment of long-term impairments following Traumatic Brain Injury, aiming to improve diagnostic accuracy and monitoring of affected individuals (80). Due to limited TBI speech data, the study addressed the over fitting problem using three learning methods: transfer learning, multi-task learning, and meta-learning. Three backbone models with different input dimensions and bottleneck-feature sizes were employed. The cascading network used a sliding window on raw audio to format input shapes, combining sequential features from the backbone models. A Gated Recurrent Unit (GRU) layer and Fully Connected (FC) layer with sigmoid activation for binary classification and linear activation for regression were used. The proposed methods significantly mitigated over fitting, improving 34% of classification accuracy of TBI and TBI regression error by 31%. A diagnostic methodology for sports-related mTBIs was proposed utilizing a Bi-LSTM-A structure that was particularized to focus on the features of MFCC for improving accuracy in detection accuracy (81). The study involved 46 rugby athletes, 7 with mTBIs. Parameters included a 44.1 kHz sample rate, default Librosa values (13 cepstral coefficients, 2048 FFT window length, 512 hop lengths). The Bi-LSTM-A model, optimized with particle swarm optimization, achieved 89.5% accuracy, with a sensitivity of 94.7% and specificity of 86.2%. The study suggests the model as a reliable mobile-based diagnostic tool for traumatic brain injuries. A DL framework was presented using data from smartphone sensors for TBI detection, introducing the TBI Bio score concept (82). The data of smartphone sensor (accelerometer, magnetometer, gyroscope, pedometer, pressure, altitude, accessibility) from subjects after head injuries was included in the dataset. The framework involved four stages: 1. Feature Creation with data collection, preprocessing, segmentation, and statistical feature extraction, 2. Attention scores of Feature fusion, 3. DL modeling for accurate TBI detection, and 4. Bioscore generation. Sliding windows of varying sizes (1, 2, or 3 days) were used for segmentation. Stacked LSTMs with Self-attention achieved 90.2% accuracy, with an 83.3% True Positive Rate. The Bioscore of TBI quantifies the probability of a person having TBI based on smartphone-sensed behavior, social interactions, mobility, and communication patterns. The study highlights the potential of passive smartphone phenotyping for TBI diagnosis.

Hybrid CNN Models

Early TBI detection was aimed to be improved using a multiple input architecture that integrated convolutional neural networks and LSTM (83). The study utilized a murine preclinical model dataset obtained from a home cage automated system, recording behaviors over five weeks. Variables such as distance traveled, body temperature, separation from other mice, and movement were recorded every 15 minutes for 72 hours weekly. The deep learning model was found to outperform other algorithms (SVM, random forest, feed forward neural network), addressing class imbalance and employing leave-one-out cross-validation. The findings suggest the potential of the proposed model for enhanced TBI detection in murine models. While the above paper used CNN + LSTM only for early detection of mTBI, the early detection of mTBI used wide field optical imaging and deep learning in this paper (84). It used calcium imaging data from mice to capture spatial and temporal features for accurate classification. For each trial, 9 samples sized at 5x100x100x1 were generated. Two main models were used: CNN-LSTM and 3D CNN. The optimizer was stochastic gradient descent. CNN-LSTM had three convolution layers followed by FC layers and performed best. 3D CNN included two 3D convolution layers and FC layers. The baseline CNN had three convolution layers. Results showed CNN-LSTM and 3D CNN outperformed the baseline CNN and SVM models, highlighting the importance of temporal information. A framework for the early mild traumatic brain injury (mTBI) detection was developed using the wide field optical imaging and the calcium imaging data from the Thyl-GCaMP6s transgenic mice (85). The core of the framework was a Convolutional Auto encoder (CAE) with three 2D convolution layers (kernel sizes 5×5, 5×5, 3×3; filter sizes 8, 16, 32) and a fully connected layer with a latent vector of 32, 64, or 128 neurons. The CAE outperformed a conventional CNN in classification accuracy (96.47%). Training used Adam optimizer, Mean Squared Error loss, over 20 epochs with a batch size of 64. Integrated with Support Vector Machines, the CAE demonstrated superior mTBI identification, showcasing its potential as a valuable tool for early diagnosis. Dysarthria detection was addressed using CNN LSTM architecture on 9184 audio recordings from the TORGO dataset (86). One twenty eight features were extracted using MFCC. The neural network, which included 25 layers - four CNN layers, max-pooling layers, three fully connected layers, and an LSTM layer for temporal information extraction, was trained using the Adam optimizer of 0.0001 learning rate. A state-of-the-art accuracy of 99.59% was achieved by the model, surpassing machine learning models (CNN-SVM, Random Forest, XGBoost, and Decision Tree). This highlights the superiority of deep learning models in dysarthria detection. A dataset of 529 records with 71 variables from TBI patients was utilized (87). Preprocessing included handling missing values, and a neural network approach with Multilayer MLP and CNN architectures was employed. The MLP had a dropout layer separated into two dense layers (16 neurons each). The CNN featured a parallel architecture with three Conv1D layers of varying kernel sizes. Training parameters were optimized, considering imbalanced data, and models achieved a high accuracy of 0.845 and an AUROC curve of 0.911. The study suggests the effectiveness of neural networks in predicting outcomes for TBI patients.

RBF

The mechanical details of TBIs were investigated, especially in terms of how something described as the angle of incidence of a hit that causes the rotation of the brain impacts something known as the Cumulative Strain Damage Measure (CSDM) values (88). To do this, they used a hi-tech computer model of the human head called SIMon v4.0, which includes parts like the cerebrum, cerebellum, and brain stem. They did 250 simulations where they applied rotational impacts of different strengths and directions. This involved looking at various angles to understand how the direction of the hit influences the damage measure. For the simulations, they used powerful software called LS-DYNA 971 Rev. 2, and to make sense of the data, they used a kind of computer model called a radial basis neural network (RBF). This helped them figure out the complex connections between how the head rotates and the resulting damage.

Table 4: Deep Neural Networks for TBI Detection with Other Types of Input Data

Authors	Dataset	Architecture	Technique	Performance
Lee *et al.,* (17)	TMS–EEG data collected from patients with DoC and resting-state EEG data	-5 convolutional layers with 2D filters -Max-pooling layers -Softmax layer	(ECI) using a CNN	ECI was effective in discriminating altered states of consciousness.
Li *et al.,* (45)	Data collection from a Taiwan based epidemiological study of TBI 12,640 cases	MLP: typical feed-forward backpropagation neural network 3-layer topology 11-node input, 7-node hidden, 1-node output layer. Sigmoid activation function		The neural network models outperforms in both the areas of ROC curl and calibration. MLP ROC area- 0.897 RBF ROC area- 0.880

Mansour *et al.,* (61) .				DL-ICH sensitivity (92.67-94.52%), specificity (94.81-96.34%), precision (94.42-96.10%), accuracy (94.10-96.03%). A comparative classification performance with WA-ANN, U-Net, SVM, WEM-CNN, CNN, andResNexT, underscored the DL-ICH model's superiority in terms of sensitivity and specificity
Marcano-Cedeño *et al.,* (62)	The data used were obtained from the PREVIRNEC platform. 10191 task executions related to the cognitive function of memory from 250 patients with medium cognitive affectation.			Decision tree: 90.38% MLP: 78.7% GRNN: 75.96% The evaluation of the models included specificity, sensitivity, and accuracy analysis, along with a confusion matrix analysis. The validation process employed cross-validation with ten folds.
Shi *et al.,* (63)	Taiwan National Health Insurance (BNHI).	Feed-forward, back propagation NN Feed-inlayer- source nodes Invisible layer Yield layer- neurons	ANN	Accuracy ANN: 95.23% LR: 82.44% AUC ANN: 89.61% LR: 77.39% ANN models outperformed logistic regression.
Rughani *et al.,* (64)	The dataset, sourced from the National Trauma Data Bank (NTDB) 200,000 records from 712 hospitals.	Feedforward 3-layer neural network Thirty ANNs were trained simultaneously	ANN	ANNs outperformed both neurosurgeon clinicians and logistic regression models. Accuracy, sensitivity, and discrimination, AUROC were superior for ANN
David lu *et al.,* (65)	Data from 115 adult patients with medium level TBI presenting in trauma centers. 250 simulations where they			ANN Accuracy: 96.13% NB model AUC of 90.14%

	applied rotational impacts of different strengths and directions.			
Segal *et al.,* (66)	NIDILRR, Patient count of 1644 in the system of TBI model database after 1 year of injury.	3 main layers: input, hidden and output layer	ANN	If FIM and DRS scores lead to the result of less severity of injury, patients lost to follow-up.
Cai *et al.,* (67)	Modified head impacts count 58, including 25 shocks and 33 non-trauma cases	Five fully connected and ReLU activation layer Sigmoid function ADAM optimizer Stochastic gradient descent		DL achieved better accuracy for cross-validation, sensitivity, AUC, demonstrating its effectiveness in concussion prediction.
Salsabilian *et al.,* (68)	40 constructed images taken from department of Cell Biology and Neuroscience at Rutgers University Node embedding features extracted using Node2vec algorithm	Two layers each for full connection and convolution. Max-pooling and ReLU layers Output layer Attrition rate: 0.25 Regularization for weight:5×10^(-4) Adaptive learning rate : 0.001	2D CNN	2D-CNN: 95.8% and graph node embedding method couldn't differentiate between normal and mTBI networks.
Salsabilian *et al.,* (69)	Cortical activities PSD (wide field calcium imaging) was examined	Frequency-specified functional networks. Frequency lower level less than 1Hz and higher level in range of 1 Hz to 8 Hz	CNN	Average classification accuracy of 97.28%. Frequency accuracy of classification of the higher band was greater.
Guimarães *et al.,* (70)	529 records with 71 variables of TBI patient from Hospital in Brazil	**-CNN1**: 3 blocks Parallel architecture Every block with 2 Convolution, Flattened layer, ReLU function, discontinuation layer of 0.2 factor -Convolutional Neural Network 2 : 2 blocks of	CNN	Accuracy: 0.859 Area under the ROC: 0.911 CNN proved to be more accurate than all other ML algorithms

		convolutional layer, serial architecture Batch normalization, ReLU function discontinuation layer, of 0.2 factor		
Koochaki *et al.,* (71)	Wide field optical imaging of cortical activity Image representation using a BoVw technique Experiments.	For ViT: Twelve layers each of hidden aspect and attention head Batch size: 8 Learning rate: 2e−5 Weight decay: 0.01, CNN model: three convolution and two fully connected layer; Softmax layer	Vision Transformer (ViT) and CNN	ViT and BoVW models outperformed CNNs in classification accuracy showcasing their potential for mTBI identification.
Wu *et al.,* (72)	Two impact datasets of size 110 and 53: Football in college, boxing, and martial arts Artificial impacts from the NFL	32 filters of sizes 3x10, 1x10, and 1x5, Coefficient of determination (R^2) :0.937 Root mean squared error (RMSE): 0.018	CNN	CNN-based approach proved to be efficient in estimating the brain strains from head impact kinematics
Wu *et al.,* (73)	Two public databases used for collecting head impact kinematics	Evaluation of three training strategies: ● baseline ● transfer learning ● combined training (combining previous training data)	CNN	Favorable outcome rate of 60.5% and 94.8% for element wise MPS of CNN
Asogbon *et al.,* (74)	High-density surface electromyography (HD-sEMG) recordings of five male TBI patients: age range of 27 to 34 years	-Input layer (L1) -Two convolutional layers -One fully connected layer (F4) -Output layer (O5) -ReLU activation functions -Max pooling layer -Dropout regularization -Adam optimizer and cross-entropy loss function were utilized	Fully connected CNN	TBI_3 achieved the highest accuracy at 98.92%, outperforming TBI_5, TBI_4, TBI_1, and TBI_2
Lin *et al.,* (75)	Linear scaling factors with 3 anatomical axes were used additionally to inputs of CNN	Randomly scaling the WHIM training samples; pairing it with augmented head impacts	CNN model on the anisotropic WHIM V1.0	Success rate for responses of scaled model is 86.2% and testing of independent models is 92.1% -successful estimations for the generic WHIM

Roy *et al.,* (76)	Imaging data was collected for 14 individuals with TBI and 12 controls, scanned at three-time frames. Glasgow Coma Scale (GCS) was used	Motion improvement, normalization, and annoyance signal regression Connectivity analysis of strength revealed heightened global connectivity at Time-2	BOLD-fMRI	Lesion analysis identified trauma lesions in 13 out of 14 cases
Hsu *et al.,* (77)	Bright-field microscopy used for images of Iba1-stained microglia from two brain regions	Three convolutional, ReLU, full connectivity and Max pooling layers Softmax output	CNN3CL	-Validation accuracy: 67.7% -F1 score: 0.64 for Resnet18 with 60 epochs. -CNNs can accurately identify resting and activated microglia
Ilyas *et al.,* (78)	924 videos of TBI patients engaged in cognizable, physio, and social improvement activities The CNN with a pretrained VGG16-CNN, extracted facial features, and the LSTM exploited temporal relations based on the extracted features	Detection of face, landmarks and tracking were performed using the SDM, followed by FQA. The CNN with a pre-trained VGG16-CNN model, extracted facial features, and the LSTM exploited temporal relations based on the extracted features	CNN and LSTM	The TBI-FER model outperforms Pepper-FER with 91% accuracy on traumatic brain injuries and extended Cohn-Kanade databases.
Nayebi *et al.,* (79)	The study collected the data of patients from 18 academic levels across the United States 110 clinical variables			RNN (AUC): 0.86 IMPACT model: 0.69 RNN model outperforms the existing IMPACT model in terms of performance metrics, including AUC, F1 score, and Kendall's correlation coefficient.
Apiwat *et al.,* (80)		GRU layer, FC layer Sigmoid activation Linear activation	DNN	
Wall *et al.,* (81)	MFCC features were extracted using Librosa, and the Bi-LSTM-A model	The parameters defined have (i) the sampling rates, (ii) the coefficients of cepstral, (iii) FFT length of window, and (iv) hop length. The sample rate for every recorded output was	deep learning Bi-LSTM-A	Accuracy: 89.5% Sensitivity: 94.7% Specificity: 86.2%

		set at 44.1kHz, maintaining uniformity across all instances.		
Asani *et al.,* (82)	TBI Bioscore determined using phone sensor data (accelerometer, gyroscope, pedometer, accessibility, etc.)	(1) Feature Creation sub-stages: (a) Data gathering and Pretreating, (b) Data decomposition and, (c) statistical feature removal (2) Feature fusion (3) DL model to detect TBI, (4) Bioscore generation	Deep Learning framework	True positive rate Accuracy of 90.2%
Teoh *et al.,* (83)	Dataset, obtained from a HCA system	A deep learning model was utilized using variables like distance traveled, temperature of body, and movement for 15 minutes for 72 hours weekly	LSTM integrated architecture	The proposed deep learning model demonstrated superior performance, showcasing its potential in detecting brain trauma in mice
Koochaki *et al.,* (84)	Imaging of calcium from mice to capture spatial features and temporal features.	2 models used: CNN-LSTM: 3 convolutional layers, FC layer 3D CNN: 3D convolutional layers, FC layers Stochastic gradient descent optimizer		CNN-LSTM > 3D CNN > CNN (baseline) and SVM (baseline).
Koochaki *et al.,* (85)		2D convolutional layers FC layer ReLU activation layer Adam optimizer MSE as loss function		CAE surpassed the conventional CNN in classification accuracy (96.47%) When integrated with Support Vector Machines (SVM), it showed superior performance for mTBI identification.
Vora *et al.,* (86)	128 features from audio files	4 layers of convolutional with max-pooling and ReLU activation. 3 FC layers. Normalization and Dropout layers LSTM layer Sigmoid activation layer		

Guimaraes *et al.,* (87)	529 records with 71 variables	1-dimensional neural network MLP comprised two dense layers separated by a dropout layer, sigmoid function and normalization	CNN with MLP	0.845 accuracy score Area under the ROC curve of 0.911.

Results and Discussion

Deep learning models have emerged to be revolutionary instruments in the discovery, classification, and analysis of traumatic brain injuries (TBI), significantly beating traditional and even machine learning methodologies. These have consistently shown capabilities to handle such diverse and complicated data types of EEG, CT, and MRI images, which hold the key to accurate diagnosis and explanation of TBI. CNN models have been used in studies related to EEG; they have been tested on accuracy levels necessary for identifying the severity of TBIs. The architectures built and optimized for the model used batch normalization, pooling layers, and ADAM optimizers, and therefore 99.76% accuracy was effectively realized. The key thing is that such models are capable of recognizing some very tiny but abnormal patterns within the brainwave that lead to TBI. Models such as LSTM and Fourier Transform derived models have successfully demonstrated impressivepredictive accuracy to differentiate between states of TBI, stroke, and normal brain. This reflects on the adaptability of deep learning algorithms in processing and filtering neurophysiological signals. In addition, EEG data has helped in developing a noninvasive method for early diagnosis and follow-up changes in the activity in the brain over time, thereby making it helpful in diagnosing TBI. In fact, deep-learning techniques have shown promising performance when dealing with tasks of brain lesion identification and segmentation, particularly subdural hematomas, intraparenchymal hemorrhages, and perilesional edema. Some architecture, such as VGG-SE-PCR, EfficientNet, and DeepMedic, have shown extremely good performance in several cases, yielding classification accuracies above 98%. They have achieved very good sensitivity and specificity values in distinguishing between different subtypes of hemorrhages, and many lesion volumes with clinical impact were detected well. After integrating multiclass segmentation with post-processing techniques, the performance was enhanced with regard to precision in lesion detection, making further use of deep learning as a must-have tool in TBI clinical management. Moreover, the enhancements like CNNs based on tracklets formation have made a lot of studies that have enabled dynamic real-time analytics, thereby improving the diagnostic workflow in emergency situations. Great advances in the field of MRI study also provided new proofs on the role of deep learning in the TBI research. Sophisticated architectures like Inception modules, 3D-CNNs, and variants of U-Net proved to be great assets in segmenting complex brain structures, in detection of lesion, and, lastly, in predicting how severe the TBI would be. The use of Inception modules during the processing of multi-contrast MRI multiplies its efficacy in overcoming problems such as exaggeration and false positives. Meanwhile, 3D-CNNs have demonstrated a lot of promise in bringing lesion segmentation to the next level by being quite out of the ordinary, with increased sensitivity and accuracy, using volumetric information. Different models, such as Patch-CNN and DeepMedic, are already the forerunners in the detection of subtle abnormalities, among other things, like cerebral microbleeds, the most critical biomarkers in the TBI prognosis. The versatility of such models to engage many other imaging modalities like susceptibility-weighted imaging and quantitative susceptibility mapping demonstrates quite well the comprehensiveness of these tools in diagnosing problems. Collectively, these findings undergird the potential of deep learning to revolutionize TBI research and clinical practices. Large-scale, diverse data sets have driven not only advancements in diagnostic capability but also new insights into pathophysiology itself. The flexibility in incorporating new data sources and continually evolving computational methods will keep deep learning front and center in both diagnosing and therapeutic innovations in TBI.

Challenges

A major problem with the development of DL models for TBI detection is the sharing of data, which is a significant barrier. Since medical imaging data is highly sensitive and is often distributed across a variety of organizations, access to this data is highly restricted. This explains why medical AIs are less accurate – the data needed to develop a proper deep learning model is simply not present. Moreover, the absence of sufficient data to work with opens the door for over fitting, which in turn decreases the usability and efficacy of a model for wider patient populations. The issue of sharing data is on its own a complex topic, as it touches on ethics and the law, which in many cases is international law and so can vary across borders. This is further exacerbated by the multitude of models an individual or an organization can create in silos, making it harder to validate the effectiveness of a model through data gathered via different sources. Of course, there are many ways around this issue; federated learning allows models to be trained on numerous decentralized sources without sending raw data into the clouds. Increasing dataset diversity for your deep learning model can be achieved either through developing more synthetic data or changing the data that you already possess. Lastly, the sensitive patient data can be de-identified and we can satisfy the privacy regulation while promoting open data initiatives. These need to be tackled to enhance the AI for the detection and management of TBI.

Clinical Implications OF DL IN TBI

DL has the potential to significantly improve the management of traumatic brain injuries by filling key gaps in their diagnosis, treatment, and outcome assessment. This article focuses on how DL methods, particularly CNNs and other advanced neural networks, are capable of efficiently processing and interpreting complex medical imaging modalities like EEG, CT, and MRI. This skill of machine learning can identify hidden patterns in the input data that otherwise might not have been noticed and will lead to a better and quicker diagnosis of TBI, thereby obtaining better results by making Milder time-sensitive medical procedures. The inclusion of DL models also opens doors to personalized treatment plans. DL can help physicians personalize treatments to patients by incorporating various data types of patient demographics, imaging results, and biomarkers. The medical personalization will further advance a patient while enhancing recovery rates while limiting therapies that are deemed unnecessary. In addition, DL has an application for management's purposes as is presented in this paper. Several studies are utilizing multi-modal information to develop models which can predict the likelihood of complications, level of recovery as well as the period of recovery and diseases. This further allows clinical decision making and resource allocation. TBI DL systems promise to fulfill that medical modality because of their ability to analyze complex, multi-modal datasets integratively and accurately.

Generalizability of Dl Models for TBI Detection

The paper points out the challenges and opportunities for the generalizability of DL models across different populations of TBI, severity levels, and imaging modalities. Generalizability is a significant concern in deploying DL models effectively in real-world clinical settings. This diversity within TBI populations, from young adults with mild injuries to the elderly with severe cases, challenges DL models uniquely. The authors note that models which are well trained on a certain dataset might fail to generalize and perform well in a population that differs demographically or clinically. Variability due to age, comorbidities, or even mechanisms of injury can lead to a significant difference in the accuracy and reliability of the models. Similarly, it discusses how TBI severity influences the complexity of patterns in medical imaging data. Mild cases are likely to be subtle, and the models used to detect such slight abnormalities need to have high sensitivity, whereas severe cases are more apparent but diverse in their manifestations. It is, therefore, critical that DL models can effectively cover this spectrum of severities to be clinically useful. Multi-modal imaging modalities for TBI detection are focused upon in this paper, namely EEG, CT, and MRI. Each of these modalities captures unique aspects of brain function and structure. A DL model has to be able to integrate or adapt variations in these differences to gain good performance. Some of the potential solutions are multimodal datasets and techniques for generalization such as transfer learning, federated learning, etc. Another recommendation made in the paper is to train on larger, more diversified datasets with rigorous testing on independent datasets from diverse populations and modalities to improve model adaptability and cross-modal learning and data harmonization of pre-processing methods. Thus, the paper finds that generalizability is a difficult task that requires innovations in methodology and collaboration to make DL models both effective and reliable across different populations of TBI, severities, and imaging techniques.

Future Directions in TBI Research with Deep Learning

In the early stages of the deep learning approach to TBI, one should first attempt at developing multimodal models using varied data sources like EEG, CT, MRI, mel-frequency, and audio recordings that may further be improved upon using various DL architectures like CNNs, RNNs, LSTMs, and attention mechanisms for improved probabilities of performance. Advanced architectures including U-Net and Deep Medic should be developed to hone lesion segmentation and models that identify subtle traumatic micro bleeds from 3D imaging at very high spatial resolutions will be notable progress. Patient outcomes such as recovery trajectories or complications such as post-traumatic epilepsy could become the focus for DL-based predictive models using longitudinal datasets and relevant imaging biomarkers, such as brain strain patterns or cortical activity metrics. Portable diagnostic tools optimized for platforms like Raspberry Pi and adaptive models capable of continuous learning in dynamic environments are also important. There is another promising avenue that includes the personalization of therapeutic strategies - namely, assessments individualized and interventions tailored by TBI severity and neuroplasticity monitored during recovery via advanced imaging techniques. Automation should be the focal point of the research: automated extraction of features from raw EEG, CT, and MRI data and a focus on XAI with an emphasis on action ability from clinical insights. Increased representation of large diversified datasets with heterogeneous injury severities will further assist in generalizability, whereas training frameworks may be designed considering multiple sites across these imaging protocols along with the type of equipment employed. Finally, the ethical as well as critical regulatory challenges-mitigating biases as well as standards of health-will make it possible toward safe deployment. Following these routes, DL would revolutionize TBI research in research, bring up better clinical cares, and enter the door toward precision medicine.

Conclusion

Deep learning is changing the working environment in the field of traumatic brain injury (TBI) diagnosis and management, as far as increasing prediction and diagnosis efficiency is concerned. Due to its enabling of the automated detection of clinically relevant, highly nuanced features in medical images, deep learning is indeed revolutionizing the traditional diagnostic capabilities. The present paper puts emphasis on the possibility of these technologies making it feasible not only to detect patients with much greater accuracy but also treat them quickly and effectively with fewer risks for developing severe complications. New opportunities arise for future investigations in this regard due to the interplay between various types of biomarkers and input data. Moreover, these approaches TBI face the reshaping of the medical world with tools such as deep learning, which narrows down the enhancements needed for the extraction metrics and detection of medical images. Thus, deep learning is set to perform miracles in the realm of TBI management and improve the methods of providing precise, adaptable and timely healthcare.

Abbreviations

TBI: Traumatic Brain Injury, DL: Deep Learning, CNN: Convolution Neural Network, MLP: Multi-Layer Perceptron, RNN: Recurrent Neural Network, ANN: Artificial Neural Network, GCS: Glasgow Coma Scale, PCSS: Providers Clinical Support System, MRI: Magnetic Resonance Imaging, CT: Computed Tomography, KNN: k-nearest neighbors, SVM: Support Vector Machine, EEG: Electroencephalogram.

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Conception and design of the work, Dr. Prabhuraj and Dr. Varalakshmi M; Data collection, analysis, Interpretation, Omm Malhotra and Hardik Bhawnani; Manuscript Preparation, Anusha Garg, Riddhi Panchal, Shreya Sonawane, Critical revision of the article, Dr. Thilagavathi M and Dr. Varalakshmi M; Final approval of the version to be published, Mr. P U Peer Mohamed. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

Ethics Approval

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References

1. National Institute of Neurological Disorders and Stroke (NINDS). Traumatic Brain Injury (TBI). Bethesda (MD): National Institutes of Health; c2023. Available from: https://www.ninds.nih.gov/health-information/disorders/traumatic-brain-injury-tbi
2. Galgano M, Toshkezi G, Qiu X, Russell T, Chin L, Zha LR. Traumatic brain injury: current treatment strategies and future endeavors. Cell Transplantation. 2017 Jul; 26(7):1118-1130.
3. National Institute of Child Health and Human Development. Bethesda: U.S. Department of Health and Human Services; c2023. Available from: https://www.nichd.nih.gov/health/topics/tbi/conditioninfo/effects
4. Vidhya V, Gudigar A, Raghavendra U, Hegde A, Menon GR, Molinari F, Ciaccio EJ, Acharya UR. Automated detection and screening of traumatic brain injury (TBI) using computed tomography images: a comprehensive review and future perspectives. Int J Environ Res Public Health. 2021 Jun;18(12):1-22.
5. National Institutes of Health. Bethesda: U.S. Department of Health and Human Services; c2016. Available from: https://www.ncbi.nlm.nih.gov/books/NBK459300/
6. National Academies of Sciences, Engineering, and Medicine. Washington (DC): National Academies Press (US); c2019. Available from: https://www.ncbi.nlm.nih.gov/books/NBK542595/
7. Katz DI, Alexander MP. Traumatic brain injury: predicting course of recovery and outcome for patients admitted to rehabilitation. Arch Neurol. 1994 Jul; 51(7):661-670.
8. N. Vutakuri. Detection of emotional and behavioral changes after traumatic brain injury: A comprehensive survey. Cognitive Computation and Systems. 2023 Mar; 5(1):42-63
9. Abujaber A, Fadlalla A, Gammoh D, Abdelrahman H, Mollazehi M, El-Menyar A. Using trauma registry data to predict prolonged mechanical ventilation in patients with traumatic brain injury: machine learning approach. PLoS One. 2020 Jul;15(7):e0235231.
10. Lin E, Yuh EL. Computational approaches for acute traumatic brain injury image recognition. Front Neurol. 2022;13:1-12.
11. Agrawal D, Poonamallee L, Joshi S. Automated detection of intracranial hemorrhage from head CT scans applying deep learning techniques in traumatic brain injuries: a comparative review. Indian Journal of Neurotrauma. 2023;20(11):123–134.
12. Alouani AT, Elfouly T. Traumatic brain injury (TBI) detection: past, present, and future. Biomedicines. 2022 Oct;10(10):1-14.
13. Lai CQ, Ibrahim H, Abdullah JM, Azman A, Abdullah MZ. Convolutional neural network utilizing error-correcting output codes support vector machine for classification of non-severe traumatic brain injury from electroencephalogram signal. IEEE Access. 2021;9:24946-24964.
14. Lai CQ, Ibrahim H, Abd Hamid AI, Abdullah MZ, Azman A, Abdullah JM. Detection of moderate traumatic brain injury from resting-state eye-closed electroencephalography. Comput Intell Neurosci. 2020 Mar;2020:1–10.
15. Caiola M, Babu A, Ye M. EEG classification of traumatic brain injury and stroke from a nonspecific population using neural networks. PLOS Digit Health. 2023 Jul;2(7):e0000282.
16. Lai CQ, Azman A, Abdullah JM, Ibrahim H. Convolutional neural network with hidden Markov model to identify non-severe traumatic brain injury from electroencephalography. Proc 11th Int Conf Robotics Vision Signal Process Power Appl. 2022; 829:455–460.
17. Lee M, Sanz LR, Barra A, Wolff A, Nieminen JO, Boly M, Rosanova M, Casarotto S, Bodart O, Annen J, Thibaut A. Quantifying arousal and awareness in altered states of consciousness using interpretable deep learning. Nature communications. 2022 Feb 25;13(1):1064.
18. Faghihpirayesh R, Ruf S, La Rocca M, Garner R, Vespa P, Erdogmus D, Duncan D. Automatic detection of EEG epileptiform abnormalities in traumatic brain injury using deep learning. In 43rd Annu Int Conf IEEE Eng Med Biol Soc (EMBC), 1-5 Nov 2021, Mexico. New York: IEEE; 2021. p. 302-305.
19. Vishwanath M, Jafarlou S, Shin I, Dutt N, Rahmani AM, Lim MM, Cao H. Classification of electroencephalogram in a mouse model of traumatic brain injury using machine learning approaches. In 42nd Annu Int Conf of the IEEE Eng Med Biol Soc (EMBC), 20-24 Jul 2020, Montreal. New York: IEEE; 2020. p. 3335–3338. doi:10.1109/EMBC44109.2020.9175915
20. Sutandi A, Dhillon N, Lim M, Cao H, Si D. Detection of traumatic brain injury using single channel electroencephalogram in mice. In 2020 IEEE Signal Processing in Medicine and Biology Symposium, SPMB, 5 Dec 2020, Philadelphia. New York: IEEE; 2020. p. 1-8. doi:10.1109/SPMB50085.2020.9353651
21. Vishwanath M, Jafarlou S, Shin I, Lim MM, Dutt N, Rahmani AM, Cao H. Investigation of machine learning approaches for traumatic brain injury classification via EEG assessment in mice. Sensors. 2020; 20(7):1-15.

22. Dhillon NS, Sutandi A, Vishwanath M, Lim MM, Cao H, Si D. A Raspberry Pi-based traumatic brain injury detection system for single-channel electroencephalogram. Sensors. 2021; 21(8):1-14.
23. Ellethy H, Chandra SS, Nasrallah FA. The detection of mild traumatic brain injury in pediatrics using artificial neural networks. Comput Biol Med. 2021; 135:104614.
24. Hale AT, Stonko DP, Lim J, Guillamondegui OD, Shannon CN, Patel MB. Using an artificial neural network to predict traumatic brain injury. J Neurosurg Pediatr. 2018; 23(2):219-226.
25. Wang X, Zhong J, Lei T, Chen D, Wang H, Zhu L, Chu S, Liu L. An artificial neural network prediction model for posttraumatic epilepsy: retrospective cohort study. J Med Internet Res. 2021; 23(8):1-14.
26. Ellethy H, Chandra SS, Nasrallah FA. Deep neural networks predict the need for CT in pediatric mild traumatic brain injury: a corroboration of the PECARN rule. J Am Coll Radiol. 2022; 19(6):769-778.
27. Adil SM, Elahi C, Patel DN, Seas A, Warman PI, Fuller AT, Haglund MM, Dunn TW. Deep learning to predict traumatic brain injury outcomes in the low-resource setting. World Neurosurg. 2022; 164:e8-e16.
28. Monteiro M, Newcombe VFJ, Mathieu F, Adatia K, Kamnitsas K, Ferrante E, Das T, Whitehouse D, Rueckert D, Menon DK, Glocker B. Multiclass semantic segmentation and quantification of traumatic brain injury lesions on head CT using deep learning: an algorithm development and multicentre validation study. Lancet Digit Health. 2020;2(6):e300–e311
29. Phaphuangwittayakul A, Guo Y, Ying F, Dawod AY, Angkurawaranon S, Angkurawaranon C. An optimal deep learning framework for multi-type hemorrhagic lesions detection and quantification in head CT images for traumatic brain injury. Appl Intell. 2022; 52(7):7320-7338.
30. Gautam A, Raman B. Towards effective classification of brain hemorrhagic and ischemic stroke using CNN. Biomed Signal Process Control. 2021; 63:1-12.
31. Remedios S, Roy S, Blaber J, Bermudez C, Nath V, Patel MB, Butman JA, Landman BA, Pham DL. Distributed deep learning for robust multi-site segmentation of CT imaging after traumatic brain injury. Proc SPIE Int Soc Opt Eng. 2019 Mar;10949:1-7. doi:10.1117/12.2511997
32. Zhang S, Cao T, Zhao H. Traumatic brain injury images classification method based on deep learning. In: Feng J, Zhang J, Liu M, Fang Y, editors. Biometric recognition. CCBR. 2021; 12878:157-164.
33. Rosnati M. Automatic lesion analysis for increased efficiency in outcome prediction of traumatic brain injury. In: Abdulkadir A, *et al.* editors. Machine learning in clinical neuroimaging. MLCN 2022. Lect Notes Comput Sci. 2022; 13596:141-150.
34. Pease M, Arefan D, Barber J, Yuh E, Puccio A, Hochberger K, Nwachuku E, Roy S, Casillo S, Temkin N, Okonkwo DO, Wu S, TRACK-TBI Investigators. Outcome prediction in patients with severe traumatic brain injury using deep learning from head CT scans. Radiology. 2022; 304(2):385-394.
35. Wang X, Shen T, Yang S, Lan J, Xu Y, Wang M, Zhang J, Han X. A deep learning algorithm for automatic detection and classification of acute intracranial hemorrhages in head CT scans. Neuroimage Clin. 2021; 32:1-12.
36. Mansour RF, Aljehane NO. An optimal segmentation with deep learning based inception network model for intracranial hemorrhage diagnosis. Neural Computing and Applications. 2021 Oct;33(20):13831-43.
37. MF Mushtaq, Mobeen Shahroz, Ali M. Aseere, Habib Shah, Rizwan Majeed, Danish Shehzad, Ali Samad. BHCNet: Neural network-based brain hemorrhage classification using head CT scan. IEEE Access. 2021; 9:113901–113916.
38. Jain S, Vyvere TV, Terzopoulos V, Sima DM, Roura E, Maas A, Wilms G, Verheyden J. Automatic quantification of computed tomography features in acute traumatic brain injury. J Neurotrauma. 2019;36(11):1794–1803.
39. Irene K, Masum MA, Yunus RE, Jatmiko W. Segmentation and approximation of blood volume in intracranial hemorrhage patients based on computed tomography scan images using deep learning method. In 2020 International Workshop on Big Data and Information Security, IWBIS, 17-18 Oct 2020, Depok, Indonesia. New York: IEEE; 2020. p. 65-72. doi:10.1109/IWBIS50925.2020.9255593
40. Gan C, Dengdi Sun, Kangli Qin, Haifeng Zhao, Fang Xiao. Improved traumatic brain injury classification approach based on deep learning. In 9th International Conference on Bioinformatics and Biomedical Science, ICBBS 2020, 16-18 Oct 2020, Xiamen, China. New York: Association for Computing Machinery; 2020. p. 120-125. doi:10.1145/3431943.3432288
41. Inkeaw P, Angkurawaranon S, Khumrin P, Inmutto N, Traisathit P, Chaijaruwanich J, Angkurawaranon C, Chitapanarux I. Automatic hemorrhage segmentation on head CT scan for traumatic brain injury using 3D deep learning model. Comput Biol Med. 2022;146:105500.
42. Angkurawaranon S, Sanorsieng N, Unsrisong K, Inkeaw P, Sripan P, Khumrin P, Angkurawaranon C, Vaniyapong T, Chitapanarux I. A comparison of performance between a deep learning model with residents for localization and classification of intracranial hemorrhage. Sci Rep. 2023;13(1):7120.
43. Zou B, Mi X, Stone E, Zou F. A deep neural network framework to derive interpretable decision rules for accurate traumatic brain injury identification of infants. BMC Medical Informatics and Decision Making. 2023;23(1):1-12.
44. Zeiler FA, Mathieu F, Monteiro M, Glocker B, Ercole A, Beqiri E, Cabeleira M, Stocchetti N, Smielewski P, Czosnyka M, Newcombe V, Menon DK; CENTER-TBI High-Resolution ICU (HR ICU) Sub-Study Participants and Investigators. Diffuse intracranial injury patterns are associated with impaired cerebrovascular reactivity in adult traumatic brain injury: a CENTER-TBI validation study. J Neurotrauma. 2020;37(14):1597–1608.
45. Li YC, Liu L, Chiu WT, Jian WS. Neural network modeling for surgical decisions on traumatic brain injury patients. Int J Med Inform. 2000;57(1):1–9.
46. Roy S, Butman J, Chan L, Pham DL. TBI contusion segmentation from MRI using convolutional neural networks. In IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018), 4-7 Apr 2018,

Washington, DC. New York: IEEE; 2018. p. 158-162. doi:10.1109/ISBI.2018.8363545
47. Pomiecko K, Sestili C, Fissell K, Pathak S, Okonkwo D, Schneider W. 3D convolutional neural network segmentation of white matter tract masks from MR diffusion anisotropy maps. In2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019) 2019 Apr 8 (pp. 1-5). IEEE. doi:10.1109/ISBI.2019.8759575
48. Chou Y, Chang C, Remedios SW, Butman JA, Chan L, Pham DL. Automated classification of resting-state fMRI ICA components using a deep siamese network. Front Neurosci. 2022; 16:768634.
49. Roy S, Knutsen A, Korotcov A, Bosomtwi A, Dardzinski B, Butman J. A deep learning framework for brain extraction in humans and animals with traumatic brain injury. In IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018), 4-7 Apr 2018, Washington, DC. New York: IEEE; 2018. p. 687–691. doi:10.1109/ISBI.2018.8363667
50. Gilbert N, Bernier RA, Calhoun VD, Brenner E, Grossner E, Rajtmajer SM, Hillary FG. Diminished neural network dynamics after moderate and severe traumatic brain injury. PloS one. 2018 Jun 8;13(6):e0197419.
51. De Feo R, Hämäläinen E, Manninen E, Immonen R, Valverde JM, Ndode-Ekane XE, Gröhn O, Pitkänen A, Tohka J. Convolutional neural networks enable robust automatic segmentation of the rat hippocampus in MRI after traumatic brain injury. Front Neurol. 2022;13:820267.
52. Koschmieder K, Paul MM, van den Heuvel TLA, van der Eerden AW, van Ginneken B, Manniesing R. Automated detection of cerebral microbleeds via segmentation in susceptibility-weighted images of patients with traumatic brain injury. Neuroimage Clin. 2022;35:103027.
53. Kamnitsas K, Ledig C, Newcombe VFJ, Simpson JP, Kane AD, Menon DK, Rueckert D, Glocker B. Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation. Med Image Anal. 2017;36:61–78.
54. Yeboah D, Nguyen H, Hier DB, Olbricht GR, Obafemi-Ajayi T. A deep learning model to predict traumatic brain injury severity and outcome from MR images. In IEEE Conference on Computational Intelligence in Bioinformatics and Computational Biology (CIBCB 2021), 13-15 Oct 2021, Melbourne, Australia. New York: IEEE; 2021. p. 1-6. doi:10.1109/CIBCB49929.2021.9562848
55. Cao M, Wu K, Halperin JM, Li X. Abnormal structural and functional network topological properties associated with left prefrontal, parietal, and occipital cortices significantly predict childhood TBI-related attention deficits: A semi-supervised deep learning study. Frontiers in Neuroscience. 2023; 17:1128646.
56. Liu S, Utriainen D, Chai C, Chen Y, Wang L, Sethi SK, Xia S, Haacke EM. Cerebral microbleed detection using Susceptibility Weighted Imaging and deep learning. Neuroimage. 2019;198:271-282.
57. Jiang J, Dai C, Liu X, Dai L, Li R, Ma K, Xu H, Zhao F, Zhang Z, He T, Niu X, Chen X, Zhang S. Implantation of regenerative complexes in traumatic brain injury canine models enhances the reconstruction of neural networks and motor function recovery. Theranostics. 2021;11(2):768-788.
58. Liu Y, Nacewicz BM, Zhao G, Adluru N, Kirk GR, Ferrazzano PA, Styner MA, Alexander AL. A 3D Fully Convolutional Neural Network With Top-Down Attention-Guided Refinement for Accurate and Robust Automatic Segmentation of Amygdala and Its Subnuclei. Frontiers in Neuroscience. 2020;14:1-13.
59. Cai Y, Ji S. Combining deep learning networks with permutation tests to predict traumatic brain injury outcome. In: Crimi A., Menze B., Maier O., Reyes M., Winzeck S., Handels H. (editors). International Workshop on Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries, 17 Oct 2016, Athens, Greece. Lecture Notes Comput Sci. Cham: Springer; 2016. p. 259-270. doi:10.1007/978-3-319- 55524-9_24
60. Rashid T, Abdulkadir A, Nasrallah IM, Ware JB, Liu H, Spincemaille P, Romero JR, Bryan RN, Heckbert SR, Habes M. DEEPMIR: a deep neural network for differential detection of cerebral microbleeds and iron deposits. Sci Rep. 2021;11(1):14124.
61. Mansour RF, Aljehane NO. An optimal segmentation with deep learning-based inception network model for intracranial hemorrhage diagnosis. Neural Comput Appl. 2021;33:13831-13843.
62. Marcano-Cedeño A, Chausa P, García A, Cáceres C, Tormos JM, Gómez EJ. Data mining applied to the cognitive rehabilitation of patients with acquired brain injury. Expert Syst Appl. 2013;40(4):1054-1060.
63. Shi HY, Hwang SL, Lee KT, Lin CL. In-hospital mortality after traumatic brain injury surgery: a nationwide population-based comparison of mortality predictors used in artificial neural network and logistic regression models. Journal of Neurosurgery. 2013;118(4):746-752.
64. Rughani AI, Dumont TM, Lu Z, Bongard J, Horgan MA, Penar PL, Tranmer BI. Use of an artificial neural network to predict head injury outcome. Journal of Neurosurgery. 2010;113(3):585-590.
65. Lu D, Li T-C, Tu Y-K, Tsai J-C, Lai H-S, Kuo L-T. Predicting long-term outcome after traumatic brain injury using repeated measurements of Glasgow Coma Scale and data mining methods. J Med Syst. 2015;39:187.
66. Segal ME, Goodman PH, Goldstein R, Hauck W, Whyte J, Graham JW, Polansky M, Hammond FM. The accuracy of artificial neural networks in predicting long-term outcome after traumatic brain injury. Journal of Head Trauma Rehabilitation. 2006;21(4):298-314.
67. Cai Y, Wu S, Zhao W, Li Z, Wu Z, Ji S. Concussion classification via deep learning using whole-brain white matter fiber strains. PLoS One. 2018;13(5):1-15.
68. Salsabilian S, Najafizadeh L. Detection of Mild Traumatic Brain Injury via Topological Graph Embedding and 2D Convolutional Neural Networks. In 42nd Annu Int Conf IEEE Eng Med Biol Soc (EMBC 2020), 20-24 Jul 2020, Montreal. New York: IEEE; 2020. p. 3715-3718. doi:10.1109/EMBC44109.2020.9175800
69. Salsabilian S, Bibineyshvili Y, Margolis DJ, Najafizadeh L. Identifying mild traumatic brain injury using measures of frequency-specified networks. Journal of neural engineering. 2022 Oct 11;19(5):056033.

70. Guimarães KAA, de Amorim RLO, Costa MGF, Costa Filho CFF. Predicting early traumatic brain injury mortality with 1D convolutional neural networks and conventional machine learning techniques. Informatics in Medicine Unlocked. 2022; 31:100984.
71. Koochaki F, Najafizadeh L. Identifying Mild Traumatic Brain Injury via Vision Transformer and Bag of Visual Features. In 11th International IEEE/EMBS Conference on Neural Engineering (NER), 24-27 Apr 2023, Baltimore, MD, USA. New York: IEEE; 2023. p. 1-4. doi:10.1109/NER52421.2023.10123771
72. Wu S, Zhao W, Ghazi K, Ji S. Convolutional neural network for efficient estimation of regional brain strains. Sci Rep. 2019; 9:1-15.
73. Wu S, Zhao W, Barbat S, Ruan J, Ji S. Instantaneous Brain Strain Estimation for Automotive Head Impacts via Deep Learning. Stapp Car Crash J. 2021; 65:139-162.
74. Asogbon MG, Samuel OW, Nsugbe E, Jarrah Y, Obe O, Geng Y, Li P. A Deep Learning based Model for Decoding Motion Intent of Traumatic Brain Injured Patients using HD-sEMG Recordings. In IEEE International Workshop on Metrology for Industry 4.0 and IoT (MetroInd4.0 and IoT), 7-9 Jun 2021, Rome, Italy. New York: IEEE; 2021. p. 609-614. doi:10.1109/MetroInd4.0IoT51437.2021.9488440
75. Lin N, Wu S, Ji S. A Morphologically Individualized Deep Learning Brain Injury Model. J Neurotrauma. 2023; 40(19-20):2233-2247.
76. Roy A, Bernier RA, Wang J, Benson M, French JJ Jr, Good DC, Hillary FG. The evolution of cost-efficiency Roy A, Bernier RA, Wang J, Benson M, French JJ Jr, Good DC, Hillary FG. The evolution of cost-efficiency in neural networks during recovery from traumatic brain injury. PLoS One. 2017; 12(4): e0170541.
77. Hsu CH, Agaronyan A, Katherine R, Kadden M, Ton HT, Wu F, Lin YS, Lee YJ, Wang PC, Shoykhet M, Tu TW. Classification of Activated Microglia by Convolutional Neural Networks. In IEEE Biomed Circuits Syst Conf, 13-15 Oct 2022, Taipei, Taiwan. New York: IEEE; 2022. p. 198-202. Doi: 10.1109/BioCAS54905.2022.9948635
78. Ilyas CMA, Schmuck V, Haque MA, Nasrollahi K, Rehm M, Moeslund TB. Teaching Pepper Robot to Recognize Emotions of Traumatic Brain Injured Patients Using Deep Neural Networks. In 28th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN), 14-18 Oct 2019, New Delhi, India. New York: IEEE; 2019. p. 1-7. doi:10.1109/RO-MAN46459.2019.8956445
79. Nayeri A, Tipirneni S, Foreman B, Ratcliff J, Reddy CK, Subbian V. Recurrent Neural Network based Time-Series Modeling for Long-term Prognosis Following Acute Traumatic Brain Injury. AMIA Annu Symp Proc. 2022; 2021:900-909.
80. Apiwat D. Speech-based Traumatic Brain Injury (TBI) Assessment using Deep Learning Methods with Limited Labeled Data. M.S. thesis, Worcester Polytechnic Institute; 2021. https://digital.wpi.edu/show/7w62fc038
81. Wall C, Powell D, Young F, Zynda AJ, Stuart S, Covassin T, Godfrey A. A deep learning-based approach to diagnose mild traumatic brain injury using audio classification. PLoS One. 2022;17(9):e0274395.
82. Asani F, Patel B, Srikanthan S, Agu E. BioscoreNet: Traumatic Brain Injury (TBI) detection using a multimodal self-attention fusion neural network and a passive bioscore monitoring framework from smartphone sensor data. Smart Health. 2023; 27:1-15.
83. Teoh L, Ihalage AA, Harp S, Al-Khateeb ZF, Michael-Titus AT, Tremoleda JL, Hao Y. Deep learning for behaviour classification in a preclinical brain injury model. PLoS One. 2022; 17(6):1-15.
84. Koochaki F, Shamsi F, Najafizadeh L. Detecting mTBI by Learning Spatio-temporal Characteristics of Widefield Calcium Imaging Data Using Deep Learning. In 42nd Annu Int Conf IEEE Eng Med Biol Soc (EMBC), 20-24 Jul 2020, Montreal, QC, Canada. New York: IEEE; 2020. p. 2917-2920. doi:10.1109/EMBC44109.2020.9175327
85. Koochaki F, Najafizadeh L. A Convolutional Autoencoder for Identification of mild Traumatic Brain Injury. In 10th International IEEE/EMBS Conference on Neural Engineering (NER), 4-6 May 2021, Italy. New York: IEEE; 2021. p. 412-415. doi:10.1109/NER49283.2021.9441130
86. Vora K, Padalia D, Mehta D, Sharma D. Hybrid CNN-LSTM network to detect Dysarthria using Mel-Frequency Cepstral Coefficients. In 5th International Conference on Advances in Science and Technology (ICAST), 2-3 Dec 2022, Mumbai, India. New York: IEEE; 2022. p. 615-621. doi:10.1109/ICAST55766.2022.10039514
87. Guimaraes KAA, Costa MGF, Amorim RLA, Filho CFFC. Comparing Prediction of Early TBI Mortality with Multilayer Perceptron Neural Network and Convolutional Neural Network. In 44th Annu Int Conf IEEE Eng Med Biol Soc (EMBC), 11-15 Jul 2022, Glasgow, Scotland, UK. New York: IEEE; 2022. p. 4457-4460. doi:10.1109/EMBC48229.2022.9871857
88. Afshari J, Haghpanahi M, Kalantarinejad R, Tafarroj MM. Proposing a Radial Basis Function and CSDM Indices to Predict the Traumatic Brain Injury Risk. IRBM. 2019; 40(4):244–252.