Brain Deformation Estimation With Transfer Learning for Head Impact Datasets Across Impact Types

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Abstract—Objective: The machine-learning head model (MLHM) to accelerate the calculation of brain strain and strain rate, which are the predictors for traumatic brain injury (TBI), but the model accuracy was found to decrease sharply when the training/test datasets were from different head impacts types (i.e., car crash, college football), which limits the applicability of MLHMs to different types of head impacts and sports. Particularly, small sizes of target dataset for specific impact types with tens of impacts may not be enough to train an accurate impact-type-specific MLHM. Methods: To overcome this, we propose data fusion and transfer learning to develop a series of MLHMs to predict the maximum principal strain (MPS) and maximum principal strain rate (MPSR). Results: The strategies were tested on American football (338), mixed martial arts (457), reconstructed car crash (48) and reconstructed American football (36) and we found that the MLHMs developed with transfer learning are significantly more accurate in estimating MPS and MPSR than other models, with a mean absolute error (MAE) smaller than 0.03 in predicting MPS and smaller than 7 s⁻¹ in predicting MPSR on all target impact datasets. High performance in concussion detection was observed based on the MPS and MPSR estimated by the transfer-learning-based models. Conclusion: The MLHMs can be applied to various head impact types for rapidly and accurately calculating brain strain and strain rate. Significance: This study enables developing MLHMs for the head impact type with limited availability of data, and will accelerate the applications of MLHMs.

Index Terms—Traumatic brain injury, brain deformation, transfer learning, head kinematics, sensor informatics.

I. INTRODUCTION

TRAUMATIC brain injury (TBI) is a major global health issue affecting over 55 million people. In the United States, it contributes to over 200,000 hospitalizations and 2.2 million emergency department visits [1]. TBI can be caused by head impacts from various sources such as traffic accidents and various contact sports including rugby, ice hockey, American football, mixed martial arts [2], [3], [4], [5], [6], [7]. To address this significant health hazard, early detection and intervention are crucial for recovery and prevention of further damage, emphasizing the need for better monitoring of TBI risks. [8], [9], [10], [11]. Previous studies [5], [6] have suggested that the presence of TBI and TBI-related pathology including diffuse axonal injury and blood-brain barrier disruption were associated with high maximum principal strain (MPS) and maximum principal strain rate (MPSR), which can be measured using wearable head impact sensor and finite element (FE) head model. [6], [12], [13], [14], [15], [16], [17], [18].

The calculation of maximum principal strain (MPS) and maximum principal strain rate (MPSR) using a finite element (FE) head model can be time-consuming due to its complicated structures and nonlinear material models. This limits the practical applications of MPS and MPSR analysis. One possible solution to speed up the calculation process is by utilizing high-performance cloud computing, as proposed by Reuben et al. [19]. Although this method significantly reduces the computational time for MPS and MPSR analysis, it still requires communication between the sensor and cloud computers. Alternatively, machine learning head models (MLHMs) have been developed to learn brain dynamics and predict MPS and MPSR from head kinematics. Alternatively, machine learning head models (MLHMs) have been developed to learn brain dynamics and predict MPS and MPSR. Three independent groups of researchers proposed MLHMs: Shim et al. [20] developed a partial least squares regression model including an impactor, a head, and a neck. The model took impact locations and speeds as inputs to predict principal strain. Wu et al. [21] developed a Convolutional Neural Network (CNN) model that predicted...
the 95th percentile MPS and MPSR from head angular velocities, and the model was further upgraded to predict the whole brain MPS and MPSR in a subsequent work [22]. Additionally, Wu et al. developed a Transformer Neural Network (TNN) to predict the time history of strain and strain rate [23]. Another group of researchers, Zhan et al. [24] proposed MLHMs that employ kinematics features extracted from multiple types of head impacts including American football (helmeted) head impacts, mixed martial arts (MMA, unhelmeted) head impacts, and lab-reconstructed head impacts. Although high accuracy was shown when the training and testing datasets are consistent, they observed a significant drop in accuracy when training and testing datasets are inconsistent. This indicated that the MLHM accuracy was significantly influenced by the type of head impact. Therefore, Zhan et al. [25, 26] investigated the differences in head kinematics across head impact types, and they found that the relationships between kinematics features and MPS and MPSR vary significantly across head impact types. This finding suggested the necessity to predict MPS and MPSR using the MLHM trained by kinematics data from consistent head impact type. In efforts to do that, Zhan et al. proposed a classification model [27] and a cluster model [28] to categorize head impacts based on kinematic features, and these models enable MPS and MPSR prediction using corresponding type-specific MLHMs.

However, developing type-specific MLHMs can be challenging if there aren’t enough head impact data available to train the deep learning model for a particular target type. In previous MLHMs, thousands of head impacts were used to train the models [21, 22, 23, 24], while only several hundred or even less than a hundred head impacts are available in some datasets [27]. Therefore, developing models with limited data is a challenging issue. One approach to overcome this limitation involves creating artificial head impact kinematics by switching the axes of the components of the original dataset [21, 22, 23, 24]. However, for some extremely small datasets, this addition of artificial head impacts is not enough. Another approach involves Principal Component Analysis (PCA) for dimensionality reduction, which reduces the number of parameters in the output layer of the MLHM and attenuates the need for extensive training data [29]. However, PCA does not adaptively influence the hidden layers of MLHM via loss back propagation, so its effect on MLHM accuracy is limited. Whilst artificially augmenting the training dataset and applying PCA techniques can be helpful, it remains challenging to develop effective MLHMs when there is insufficient head impact data available for training.

To address the issue of limited data availability, we proposed a new approach: first, we generated a large simulation dataset, referred to as the “basis dataset”, including impacts with wide ranges of impact locations, directions, and speeds. Second, we leveraged this basis dataset to develop or adapt MLHM to a specific type of head impact in which the data availability is limited. Five training strategies were used to develop type-adapted models: data fusion with/without data whitening (fusion train 1, 2), augmented data fusion with/without whitening (augmented fusion train 1, 2), and transfer learning. Additionally, three strategies were implemented as baseline models: training on the basis dataset (Pre-train), and training on the dataset for the target type of head impact with or without (target train 1, 2). All strategies were tested on four types of head impacts: college football (CF, n = 302), mixed martial arts (MMA, n = 457), reconstructed professional football (NFL, n = 36), and car accidents from National Highway Traffic Safety Administration (NHTSA, n = 48). Given the ample size of the basis dataset (n = 12,780), the accuracy of the pre-train model on the basis dataset is not constrained by dataset size, and the goal of this paper is to achieve similar or higher accuracy when compared with that on the basis dataset. The efficacy of each strategy was assessed using three evaluation metrics as followed:

1) **Accuracy on a specific dataset**: element-wise mean absolute error (MAE) on the target dataset was calculated to indicate the accuracy. We determined if the MAE of the type-adapted models on the target dataset was lower than that of the pre-train model on the basis dataset and assessed if the type-adapted models outperformed the baseline models.

2) **Influence of target dataset size**: on two datasets with more than a hundred head impacts (CF and MMA), we varied the amount of data used in training and investigated the accuracy of different training strategies and the minimum size of the training dataset.

3) **Effects of prediction accuracy on TBI detection**: based on the logistic regression risk function fitted on the NFL dataset, which contains clinical diagnoses, we tested that how the transfer learning model, which was the best strategy selected in previous evaluations, affected concussion detection accuracy, precision, and recall.

The abbreviations used in this study are listed in Table I and Table II.

### II. METHODS

#### A. Dataset Description

1) **Basis Dataset Description**: To train an accurate MLHM, we first generated a basis dataset with 12,780 simulated impacts from a validated finite element (FE) model of the Hybrid III anthropomorphic test device (ATD) headform [30]. The head model simulated impacts were regarded as the basis dataset for model development. In the basis dataset, the headform was impacted at different locations with velocities from 2 m/s to 8 m/s, which resulted in a total of 2,130 impacts [29]. The impact kinematics were processed via a second-order Butterworth low-pass filter (cut-off frequency: 150 Hz). Then, considering the symmetry, we artificially created head impacts by switching the kinematics along different axes (X: posterior-to-anterior, Y: left-to-right, Z: superior-to-inferior), which yielded 12 sets of different combinations (XYZ, YZX, XZY, ZYX, YXZ).

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**TABLE I**

| Abbreviation | Meaning |
|--------------|---------|
| TBI          | traumatic brain injury |
| FEM          | finite element modeling |
| MLHM         | machine learning head model |
| MPS          | maximum principal strain |
| MPSR         | maximum principal strain rate |
| MAE          | mean absolute error |
| TAI          | traumatic axonal injury |
| CF           | college football |
| MMA          | mixed martial arts |
| HM           | head model |
| NFL          | National Football League |
| NHTSA        | National Highway Traffic Safety Administration |
| BBB          | blood-brain-barrier |

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**AUTHOR INFORMATION**

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The abbreviations used in this study are listed in Table I and Table II.
The simulations of headform impact were performed in Sherlock High Performance Computer cluster at Stanford.

2) Target Dataset Description: A variety of different types of head impact datasets were collected to be the target datasets to evaluate the accuracy of type-adapted and baseline models: 1) 302 college football (denoted as CF) head impacts which were recorded by the Stanford instrumented mouthguard [31], [32]; 2) 457 MMA head impacts (denoted as MMA) which were recorded by the Stanford instrumented mouthguard [6], [33]; 3) 36 selected reconstructed helmeted head impacts from the National Football League (denoted as NFL) [34]; 4) 48 head impacts from automobile crashworthiness tests conducted by the National Highway Traffic Safety Administration (denoted as NHTSA) [26]. The distributions of the MPS, MPSR, peak resultant angular acceleration, and peak resultant angular velocity are shown in Fig. S1.

3) Finite Element Modeling for Reference Label Calculation: The KTH FE model (Stockholm, Sweden) [35], which is a validated FE head model with detailed structures of head and includes 4124 elements for brain, was used to calculate the MPS and MPSR as the reference for MLHMs. As for the computational cost, it usually takes 7 hours to model one impact with a computer (16 GB RAM, Intel Core i7-6800 K CPU). In this study, most of the FE simulations were performed in Sherlock High Performance Computer cluster at Stanford.

4) Kinematics Feature Engineering: In MLHM, the kinematics features were extracted from the kinematics curves and then given to the hidden layers as inputs. Kinematics features have been proven to be influential to the accuracy in our previous studies [24], [26]. Both temporal features and spectral features from the translational and rotational head movements were used in this study. The rationales of feature selection and the details of features were presented in our two previous publications [24], [28] and reviewed in the supplementary materials. Feature standardization was performed with the same implementation as that in our previous publication [24]. The feature engineering were done in MATLAB R2020a (Austin, TX, USA). The data standardization was done in Python 3.7 with scikit-learn packages [36].

B. MLHM Development

The MLHMs were developed to predict MPS and MPSR based on the same structure as our previously proposed machine learning head model with five layers. To optimize the model accuracy, the logarithmic transform was applied on the labels (MPS, MPSR) in the development of the MLHM to stabilize the residual variance and avoid negative MPS and MPSR predictions [24]. To use this transform, in the training stage, the MPS and MPSR values were transformed by taking its logarithm. In the prediction stage, the predicted values were inverse-transformed as MPS and MPSR by exponentiation. The details of MLHM development have been presented in our previous publication [24] and reviewed in the supplementary materials.

1) Performance of Basis Model on Basis Dataset: To test the performance of MLHM when the size of the training dataset is not a limitation, the basis dataset with 12,780 impacts was partitioned into 75%/15%/15% for training/validation/test respectively to develop the basis model. The size of this training dataset is significantly higher than the one in our previous study (n = 1422) [24], in which the MLHM exhibited high accuracy. Therefore we consider the basis dataset n = 12,780 to provide enough impacts that the accuracy of the model won’t be affected by the size of the dataset.

2) Baseline Models on Target Datasets: We developed the following three baseline models on the target datasets to be compared against the type-adapted models mentioned in the next section. The training/validation/test partitions for the target datasets were 50%, 25%, 25%, respectively to ensure at least 10 validation/test impacts from small datasets to provide a robust estimate of model accuracy. The model development and dataset partitions were also described in Fig. 1(b) and Table II:

1) The pre-trained model (pre-train): the MLHMs trained on the whole basis dataset and then directly used to predict the MPS/MPSR of the target test impacts. It should be noticed that even the pre-train and the basis model were both developed with the basis dataset, the pre-train model used the whole dataset while the basis model used 75%. Furthermore, the pre-train model was tested on the target dataset as the baseline, while the basis model was tested on the basis dataset in a scenario where the accuracy is not longer constrained by the dataset size.

2) The models trained on the whole target training data (target train): the MLHMs were trained on the training set partitioned from the target datasets either with both the logarithmic transform and the data whitening [24] on the labels (target train 1), or with the logarithmic transform only (target train 2).
3) Type-Adapted Models Development on Target Datasets: To improve the accuracy of MLHMs on target head impact datasets with limited data availability, we adopted five strategies to adapt MLHM to the target type Fig. 1(b). The target dataset was partitioned into 50%/25%/25% for adapting/validation/test respectively.

   Data fusion strategy: the target impacts dataset (CF/MMA/NHTSA/NFL) was firstly partitioned into 75%/15%/15% for training/validation/test respectively (Fig. 1(b)). The training data from the target dataset were fused with the basis dataset. In this way, the model can benefit from the large number of impacts from the basis dataset by learning the relationship between kinematics features and the MPS and MPSR. Furthermore, to account for the potential feature distribution variation from the basis dataset to the target dataset, we recalculation the mean and standard deviation for feature data standardization based on the union of these two datasets. We refer to this approach as data fusion because we combine the computer-simulated impacts and the target impacts. Additionally, to account for the potentially different MPS and MPSR distributions, for this strategy, in addition to the logarithmic transform, we adopted the data whitening approach according to the following formula:

   \[
   \tilde{Y}(i, j) = \frac{Y(i, j) - \text{mean}_i(Y(i, j))}{\text{std}_i(Y(i, j))}
   \]

   \(Y(i, j)\) denotes the logarithmic-transformed MPS and MPSR of the \(i\)th brain element for the \(j\)th impact. The mean\(_i(Y(i, j))\) and std\(_i(Y(i, j))\) for each of the 4124 brain elements were calculated on the combination of the basis dataset and training set of target dataset in hyperparameter tuning process, and on the basis dataset, the training and validation sets of target dataset in model evaluation. mean\(_i(Y(i, j))\) and std\(_i(Y(i, j))\) were recorded to inverse-transform the prediction of the logarithmic-transformed MPS and MPSR. The assumption was that the dataset used to calculate mean\(_i(Y(i, j))\) and std\(_i(Y(i, j))\) represented a general dataset partition: partition entire dataset into training/validation/test sets

   | Entire dataset | Training | Validation | Test |

   2. Hyperparameter tuning

   | Training | MLHM | Predict | Validation |

   3. Model Evaluation

   | Training | Hyperparameter tuning | Predict | Test |

   (b) Model development on target dataset

   Dataset Partition: partition target impacts into training/validation/test sets

   | Dataset CF/MMA/NHTSA/NFL | Training | Validation | Test |

   50% : 25% : 25% for NHTSA/NFL

   1-2X : X : X for CF/MMA X=15%, 20%, 25%, 30%, 35%

   Baseline: Pre-trained model: no fine-tuning on the target training data

   | Basis dataset | Train | Pre-trained model | Predict | Test |

   Baseline: Model trained on Target data

   | Training | Target model | Predict | Test |

   Proposed Strategies 1: Data Fusion: combine simulated impacts and target training data for training

   | Basis dataset | Train | Fusion model | Predict | Test |

   Proposed Strategies 2: Augmented Data Fusion: combine simulated impacts and augmented target training data for training

   | Basis dataset | Train | Fusion model | Predict | Test |

   Proposed Strategies 3: Transfer Learning: fine-tune the basis model with target training data

   | Basis dataset | Train | Pre-trained model | Fine-tune | Transfer model | Predict | Test |
distribution and in this way, the prediction model can also benefit from the overall distribution information. The logarithmic-transform was performed before the data whitening. In the prediction stage, the inverse-transformed MPS and MPSR need exponentiation to get the MPS and MPSR predictions.

Augmented data fusion: considering the difference in dataset size, the data fusion may suffer from the high weight put on the simulation data. To address this, we proposed the augmented data fusion strategy where the weight on the target training data was augmented to the same amount of simulation data.

Transfer learning strategy: First, we developed and optimized MLHMs using the basis dataset. The basis dataset was randomly partitioned into 70% training data for model training, 15% validation data for hyperparameter tuning and 15% test data for model performance evaluation, which is illustrated in Fig. 1. It should be noted that the MLHMs are different from the pre-train model according to the different ratios of the basis dataset used in training.

Then, upon partitioning the target impacts into training, validation, and test sets, we used the training set to fine-tune the connection weights of the basis models (Fig. 1(b)). The fine-tuning process was done by freezing the connection weights of the first 0/1/2 hidden layers and using the weights of the basis model as the new initialization before another round of training was performed on the target training impacts. It should be mentioned that when 0 hidden layers are frozen, the models are fine-tuned with the parameters initialized based on the model trained on the simulated impacts in the basis dataset. The number of frozen layers, the number of training epochs, learning rate were set as the hyperparameters, which were tuned on the target validation impacts. As the adapted models were derived from the basis models, we fine-tuned the models with fewer epochs and/or lower learning rate which led to model convergence without overfitting to the limited target training impacts. To address the potential different feature distribution, data standardization was performed based on the union of the basis dataset and the target training impacts. Data augmentation mentioned in the previous section was also used on the target training impacts before the second round of training (fine-tuning) was performed.

C. Model Evaluation

To quantify the model accuracy of the series of MLHMs we developed on various datasets (HM/CF/MMA/NHTSA/NFL), the mean absolute error (MAE) was used as the metric: the MAE between the predicted and the reference MPS/MPSR firstly averaged over 4,124 brain elements and then averaged over all test impacts (calculation details shown in [24]). Finally, the summary statistics (mean, median, STD) were calculated over 20 parallel experiments with random dataset partitions. This metric was used because it has the same unit as the MPS/MPSR for researchers to easily perceive the model accuracy and compare the error with the injury threshold. In addition, the root mean squared error (RMSE) and coefficient of determination ($R^2$) were computed to complement the MAE in the supplementary materials.

1) Model Accuracy of Type-Adapted Models: Firstly, we tested the baseline models and the type-adapted models on the four target datasets in the estimation of MPS and MPSR. We determined if the type-adapted models on the target dataset can achieve similar accuracy compared with the basis model on the basis dataset (MAE: 0.015 for MPS and 2.818 s$^{-1}$ for MPSR, see details in the Results section), and determined if the type-adapted models out-perform the baseline models.

2) Performance Variation of Type-Adapted Models With Target Training Data: Secondly, on the two target datasets (CF and MMA), we variate the percentage of target training data to show the influence of the quantities of target training data on model performances. We gradually varied the ratio of the target training, validation, and test data on two large target datasets (CF, MMA), which is referred to as “1−2X” (percentage of training data) and “X” (percentage of validation data and test data) in Fig. 1(b). The varying percentage of target training data simulated different levels of target training data scarcity. Then, with different quantities of target training data, the performances of the type-adapted models as well as the baseline models on the target dataset were tested. Furthermore, we determined the minimum quantity of the training dataset need to achieve similar accuracy compared with the basis model on the basis dataset. (MAE: 0.015 for MPS and 2.818 s$^{-1}$ for MPSR).

3) Model Performance in mTBI Detection: Concussion is the clinically diagnosed mTBI. To show how the MLHMs accuracy affects concussion risk prediction, we developed logistic regression models based on the 95th percentiles of MPS and MPSR given by FE simulation of 53 head impacts collected in professional American football (concussion: 22, no concuss: 31) [34]. First, to see how MLHMs’ accuracy affects The absolute error in the concussion risk estimation is computed. Then, according to FE simulation results, MPS and MPSR injury thresholds of 50% risk were 0.206 and 37.237 s$^{-1}$ respectively. The impact was determined to be concussive or non-concussive by comparing the MPS and MPSR given by the MLHMs and the injury threshold. The precision, recall (also known as sensitivity), and accuracy were computed to show how the performance of MLHMs accuracy affects the detection of mTBI.

4) Comparison With Simpler Statistical Learning Methods: Additionally, we compared the MLHMs with the simpler statistical learning models based on linear regression, ridge regression and K-nearest neighbor (KNN) regression. The transfer models (trained on the combination of dataset HM and any target training set), the pre-trained models (trained on dataset HM) and target train models (trained on the target training set only) were investigated, with results shown in supplementary materials.

D. Statistical Tests

To ensure robust results and test statistical significance, we did 20 parallel experiments for each prediction task and used the Wilcoxon signed-rank test to compare the accuracy (in MAE) of the models developed on the two proposed strategies and that of the baseline models. The paired t-test was not used because the Shapiro-Wilk test rejected the normal distribution assumption on some of the results; the Wilcoxon signed-rank test do not rely on the normality. The most conservative $p$-values were reported in the result sections, which held true for all the pairwise comparisons (e.g., between the transfer learning model and each of any other model), unless reported otherwise in more details.

III. RESULTS

A. Basis Model Performance on the Basis Dataset

The abbreviations for the different models in this study are shown in Table II. The basis model reached an MAE of 0.015 for MPS prediction and an MAE of 2.818 s$^{-1}$ for MPSR prediction.
Fig. 2. Model accuracy of predicting MPS and MPSR on the target impact datasets with 50% training data and 25% test data for each dataset. The mean absolute error (MAE) of the MPS prediction models on dataset NFL (a), dataset NHTSA (b), dataset CF (c) and dataset MMA (f). The MAE of the MPSR prediction models on dataset NFL (c), dataset NHTSA (d), dataset CF (g) and dataset MMA (h). Due to the large variation among different models, the MAE ranges were selected to clearly show the most accurate models. The background of the baseline models were shaded. The most conservative statistical significance in pair-wise comparison was reported for the transfer learning method: *: \( p \leq 0.05 \), **: \( p \leq 0.01 \), ***: \( p \leq 0.001 \).

on the basis dataset. The MAE for the MPS prediction was much smaller than the differences of brain strain seen in injury and non-injury cases (between 0.3 and 0.4) [35, 37]. The MAE for the MPSR prediction was also much smaller than the concussion threshold (around \( 25\text{s}^{-1} \)) [38], the threshold for accurate axonal injury prediction in large animal models (\( 120\text{s}^{-1} \)) [18] and the threshold for accurate brain contusion volume prediction in small animal models (\( 2500\text{s}^{-1} \)) [14]).

B. Improvement of Model Accuracy on Different Target Impact Datasets With Type-Adapted Models

To improve the model’s accuracy on different target impact datasets, transfer learning, data fusion and augmented data fusion models were proposed and compared with three baseline models. The results are shown in Fig. 2 and the model hyperparameters are shown in Suppl. Table S2.
Fig. 3. Model accuracy of predicting MPS and MPSR on dataset CF and dataset MMA with different percentages of training data. The mean absolute error (MAE) of the MPS prediction models on dataset CF (a) and dataset MMA (b). The MAE of the MPSR prediction models on dataset CF (c) and dataset MMA (d). Due to the huge variation among different models, the MAE ranges were selected to clearly show the most accurate models. Note that the percentage of target data used for training purposes, which is the “1–2X” in Fig. 1. The goals in MPS and MPSR estimation are marked with a concrete line and regions indicating the worse accuracy are shaded.

On dataset NFL and NHTSA with fewer than 25 training impacts, all models failed to reach the accuracy on the basis dataset (MPS MAE: 0.015, MPSR MAE: 2.818 s\(^{-1}\)). However, the transfer learning models effectively reduce the error in MPS and MPSR estimation. On dataset NFL, the median MAE based on the transfer learning MPS model was smaller than 0.025 and the median MAE based on the transfer learning MPSR prediction was smaller than 4 s\(^{-1}\). For the MPS prediction, the transfer learning model was the most accurate (\(p \leq 0.05\)). For MPSR prediction, the transfer learning model was significantly more accurate than all models but the pre-trained model (\(p \geq 0.05\)). On dataset NHTSA, the transfer learning models and augmented data fusion (Aug. fusion train 2) were the most accurate models for both MPS prediction and MPSR prediction (\(p \leq 0.001\)), with a median MPS prediction MAE smaller than 0.028 and a median MPSR prediction MAE smaller than 7 s\(^{-1}\).

On dataset CF, in MPS prediction, multiple models reached the MAE of 0.015 while the transfer learning model is significantly more accurate than other models (\(p \leq 0.001\)). In MPSR prediction, the transfer learning model is the only one achieving the accuracy of an MAE of 0.015, which is significantly better than other models (\(p \leq 0.001\)).

On dataset MMA, in MPS prediction, the transfer learning model is the only one achieving the goal of MAE while significantly outperforming other models (\(p \leq 0.001\)). In MPSR prediction, no models can reach the goal in MAE but the augmented data fusion model and transfer learning model reach the best accuracy.

To conclude, on the two datasets with fewer than 25 training samples (NFL and NHTSA), it is hard to reach an accuracy of MPS and MPSR estimation similar to that on the basis dataset but transfer learning is effective in reducing the error. On the two datasets with more than 150 training impacts (CF and MMA), it is possible to reach the accuracy on simulation data with different type-adapted models, and the transfer learning models are generally the most accurate models.

C. Model Accuracy Variation With the Percentage of Target Training Data

The model accuracy (in MAE) on the two larger target datasets (CF and MMA) with varying percentages of training data were shown in Fig. 3 (comparison with simpler statistical learning models, \(R^2\) and RMSE results shown in the Suppl. Fig. S2–S4).

On dataset CF for the MPS prediction (Fig. 3(a)), the transfer learning models were the most accurate (\(p \leq 0.01\)), with MAE smaller than 0.015, except that with 30\% CF training impacts (91 impacts) there was a weak statistical significance in comparison between the transfer learning model and the augmented data fusion model (Aug. fusion train 2) (\(p \leq 0.1\)). For the MPSR prediction, the transfer learning models were the most accurate
models, and the MAE was smaller than 3 s\(^{-1}\) at percentages of training data as well (\(p < 0.05\)) (Fig. 3(c)).

On dataset MMA, for the MPS prediction, the transfer learning models were the most accurate under four different percentages of training data (\(p \leq 0.001\)), with the MAE smaller than 0.015, with no statistical significance compared with the augmented data fusion model (Aug. fusion train 2) in the case of 30\% MMA training data (Fig. 3(b)). For the MPSR prediction, the transfer learning and the augmented data fusion (Aug. fusion train 2) were the most accurate but there was no significant difference between these two types of models under five training percentages (Fig. 3(d)).

These results indicate that the pre-training based on the basis dataset and fine-tuning based on the dataset CF/MMA can adapt the models to be at least non-inferior to all other models for the MPS and MPSR estimation of these two specific types of target data. The data-fusion-based MLHMs are inferior to the transfer learning strategy in accuracy: the models also improve the model accuracy to a limited extent, but the improvement is not guaranteed across scenarios. Compared with the MPS MLHMs we previously developed [24] with 70\% MMA training data, the transfer learning MLHMs reached a mean MAE around 0.013 and a mean \(R^2\) around 0.7, which is evidently more accurate than the previously developed MLHMs (mean MAE around 0.025, mean \(R^2\) around 0.6). Additionally, the transfer learning models were significantly more accurate than all simpler statistical learning models (Suppl. Fig. S2).

Besides the accuracy over all brain elements, we have also calculated the MAE on the brain elements based on different brain regions and the results are shown in Suppl. Table S3 and Fig. S5. The results show that overall, the MPS/MPSR models based on transfer learning show high accuracy on various brain regions, with a mean MAE smaller than 0.025 for MPS prediction and a mean MAE smaller than 5.2 s\(^{-1}\) for MPSR prediction across different brain regions. The MLHMs tended to be slightly more accurate on certain regions (brainstem, cerebellum, thalamus) but slightly less accurate on other regions (corpus callosum, midbrain), in terms of MAE. The error was well below the injury thresholds in MPS and MPSR which are mentioned previously [14], [18], [35], [37], [38].

### D. Visualization of MPS and MPSR Predictions

To visualize the model accuracy in predicting MPS and MPSR, we selected the example test impacts from dataset HM, CF, MMA, NFL and NHTSA, by firstly ranking the predictions with 95th percentile MPS and MPSR and taking the the median, and plotted the 3D brain MPS and MPSR maps given by the model predictions (Fig. 4(a)). Note that 95th percentile rather than the 100th percentile was selected to avoid potential computational artifacts from analysis [39]. Here the predictions given by transfer-learning-based MLHMs and the reference KTH model (FEM) output were compared with 3D point clouds. It can be shown from the results that, for each type of target impacts, the high-strain and high-strain-rate regions predicted by the MLHMs were similar to those output by the FEM. Besides the accuracy shown in the example 3D visualizations, we plotted the overall distributions of the predicted MPS/MPSR on the target datasets and compared them against the reference values given by the KTH model (Fig. 4(b) and (c)). It can be seen that the transfer-learning-based MLHMs predict the overall distribution of the MPS and MPSR accurately.

### E. Model Performance in the Concussion Detection

Logistic injury risk functions for concussion were developed on the NFL dataset (logistic regression curves fitted shown in the Suppl. Fig. S9). The effectiveness of transfer learning models in concussion detection was analyzed and the absolute error (AE) in risk estimation, accuracy, precision and recall are shown in Fig. 5. It should be mentioned that the reference is the concussion risk calculated based on the FE model. The results show high performance of the transfer learning models across different types of head impacts. Similar accuracy was reached by the MPS-based and MPSR-based models but the MPSR-based models reached higher recall scores while the MPSR-based models reached higher precision scores.

### IV. Discussion

In this study, we aimed to improve the accuracy of machine learning head models (MLHMs) in predicting brain strain (MPS) and strain rate (MPSR) for different types of head impacts, particularly for target datasets with limited number of impacts. To achieve this, we introduced five strategies: data fusion w/o whitening, augmented data fusion w/o whitening, and transfer learning. Our goal was to overcome the limitations of previous MLHMs that have low accuracy due to limited quantity and quality of training data. We tested the proposed strategies on target impact datasets from college football, mixed martial arts, car crashes, and the NFL. The MLHMs developed using transfer learning, where the models were pre-trained on a large dataset of head model simulated impacts and then fine-tuned with small amounts of target data, were found to be more accurate compared
in certain target impacts. Therefore, the MLHMs may overfit to the simulated head impacts, which leads to their inferior accuracy when applied to certain target impact types where the target data distribution is far different from that of the simulated impacts. With the transfer learning strategy and data fusion strategy, the MLHMs are more accurate on the smaller target datasets and the accuracy cannot be achieved by simpler, less data-hungry statistical learning models. Because researchers usually attach more significance to the model performance on target impacts, this study achieves the goal of further optimizing the target impact risk estimation accuracy for real-world applications.

Additionally, this study presents novel MPSR prediction models. While brain strain, particularly MPS, has been established as a strong predictor of TBI [6], [14], the importance of strain rate, particularly MPSR, as a complementary factor in predicting TBI cannot be ignored. Research has demonstrated that MPSR has a strong correlation with TAI, indicating that TBI is not only dependent on brain strain but also on strain rate [17], [18]. This study goes beyond MPS prediction models [21], [22], [23], [24], [40], by providing fast diagnosis through MPSR.

Moreover, like the previously developed MLHMs [21], [22], [23], [24], [40], the newly developed series of MLHMs significantly reduce the computational time cost of conventional FEM. These models can estimate MPS and MPSR within 1 ms on a personal computer, making real-time TBI risk estimation possible. This has potential applications for sport team managers and clinicians to monitor brain health for athletes using wearable technology [31], [41]. Early detection and intervention have been shown to improve patient recovery from TBI [8], and the MLHMs provide detailed, region-specific information on brain strain and strain rate, enabling more informed decisions on protective measures and medical imaging instructions. Unlike previous brain injury criteria, which only provide a summarized injury risk score, the MLHMs can predict brain strain and strain rate for every brain element and display it in a 3D map, making it easier for users to understand the TBI risks and region-specific risk information without a deep understanding of injury biomechanics.

The methods of this study is worth more discussion. In this study, the proposed strategies for better target impact MPS/MPSR predictions generally work well in reducing the prediction MAE and increasing prediction $R^2$. Although all strategies attempt to leverage the information gained from the large dataset of simulated head impacts, the transfer learning strategy outperformed the data fusion strategies in almost all the experiments in this study. This can be due to 1) the different information processing protocols of these two different strategies, and 2) how these two strategies leverage the prior knowledge unique to their methods for estimating MPS/MPSR. The data fusion strategy processes the information in parallel by directly combining the simulated impacts and the target data, while the transfer learning strategy processes the information in series by first modeling on the simulated impacts and then on the target impacts. The parallel structure generally weighs the simulated impacts and target impacts equally, while the series structure attend more to the target data because although the model parameters in the fine-tuning process are initialized based on the simulated data, the ultimate parameters of the MLHMs are determined by the target data. As a result, the transfer-learning-based models can better adapt to the target data distribution.

These different strategies leverage different prior knowledge learned from the training data. The data fusion strategies adopt
the data whitening of the labels (MPS, MPSR), which incorporates the distribution information of the simulated data and target data. The distribution of MPS and MPSR of the training data (i.e., the label distribution) can be regarded as the prior knowledge that is leveraged in the prediction. Therefore, the predictions are influenced by the MPS and MPSR distributions in the training data via the data whitening process. On the contrary, the transfer learning strategy leverages the prior knowledge stored in the model parameters (MLHM connection weights), which reflects the prior knowledge in the label distributions via data whitening, while the transfer learning strategy further leveraged the prior knowledge in the predictor-label relationship via model parameter fine-tuning.

The variations in model performance across types of target impacts indicate the difference between target data and the head model simulated impacts. For instance, the pre-trained models without fine-tuning show high accuracy on the dataset CF and dataset NFL in both MPS and MPSR predictions. There were even no statistically significant differences between the transfer learning model and the pre-trained model in MPSR prediction on dataset NFL. These results indicate that the basis dataset, CF dataset, and NFL dataset are generally similar in their data distributions. On the contrary, the pre-trained models show significantly inferior accuracy on MMA dataset in predicting MPS and MPSR, which are even less accurate than the models trained merely on the target MMA impacts. This observation indicates that the models trained on basis dataset do not apply well onto MMA impacts and the differences between these two datasets are more evident than those among the basis dataset, CF, and NFL datasets. This observation may be explained by the fact that the head model simulated impacts are generally simulated for the research of American football impacts, and therefore, the simulated impacts may better represent the characteristics shown in college football or NFL impacts [25]. Additionally, the MMA head impacts are measured without protective helmets while the football impacts are measured with protective helmets, which may effectively change the impact responses of the head [42]. The difference between MMA and other dataset reflects the different characteristics of various types of head impacts [27] and according to the results, the transfer learning is effective in capturing the distribution shifts across head impact types and enables more accurate MPS and MPSR estimation. Furthermore, for the models trained only on the target training data, the accuracy generally increases with more training data. It is possible that with adequate target data, these models can approximate the best performing transfer-learning models.

Although this study shows the effectiveness of data fusion and transfer learning in optimizing TBI risk estimation, there are limitations that need to be pointed out.

First, the brain difference and head shape variation among different individuals are not considered in this study. There have been previous studies showing that individual differences can bear significant influence on brain strain [43]. Therefore, to make the MLHMs even more accurate across different people, future studies can take other personal predictors into the models.

Another limitation of this study is that we only developed models and tested them with one finite element head model (FEHM): the KTH model. The KTH model is limited when we compare it with the state-of-the-art finite element head models (FEHM) [43], [44]. For instance, the gyri and sulci can have significant influences on the behavior of FEHM. However, they are not included in the KTH model. Future studies can focus on the development of MLHMs based on more advanced FEHM. Other FE head models have been available in recent years, but there is no evidence showing that predictability of TBI is improved in other models. So we only used the KTH model in this study. In the future, the pipeline presented in the manuscript can be applied to develop MLHMs for other FE models.

Additionally, the series of MLHMs developed in this study are based on the features extracted from the kinematics (the linear acceleration, the angular velocity, the angular acceleration, and the angular jerk). Therefore, the quality of the engineered features set an upper threshold of model performances. We adopted this feature engineering approach because: 1) these features have been shown to be very effective in aggregating the temporal and spectral information from the signals and predicting brain strain [24], [26]; 2) there are limited quantities of target data to train the end-to-end MLHMs out of the raw signals; and 3) due to the different triggering patterns, sampling rates, method of attachment to the head, recording time window lengths of various measurement devices to collect the target data and the different patterns of impact kinematics across various impact types, there may be issues such as the time mismatch of the start/peaks of the impacts collected from different devices. Therefore, with limited training data, directly feeding the signals into MLHMs may not lead to effective feature extraction. In contrast, the feature engineering approaches shown in this study can be effective to summarize the information stored in the signals which we thought could contribute to brain strain and strain rate without misleading the MLHMs with temporal details. However, as more data are available, more data-driven feature extraction approaches such as the convolutional neural network (CNN), variational autoencoder (VAE), and recurrent neural network (RNN) with long short term memory (LSTM) can be tested and applied to get more accurate models without the feature engineering step. These types of complex neural network structures are effective in extracting information with large quantities of training data without human knowledge and feature designs, and therefore may be able to further optimize the MLHMs.

It should be mentioned that the datasets we used in this study are not without limitations. Firstly, our FE-simulated dataset was based on a hybrid III dummy, which may not fully accurately represent the real human anatomy. Additionally, we augmented the simulated dataset by switching the kinematics on the three anatomical axes, which may not necessarily generate real-world-like impact kinematics. Furthermore, our NFL and NHTSA datasets were relatively small and the performance testing and model development on these datasets may suffer from high variance. Finally, in this study, we only used five impact datasets as a proof of concept. If users want to use the MLHM on other types of head impacts, another set of datasets are needed for fine-tuning.
V. CONCLUSION

This study presents optimized MLHMs that use data fusion and transfer learning to accurately predict brain strain (MPS) and strain rate (MPSR) for target impact datasets other than the simulated head impacts. Results show that transfer learning helps the MLHMs achieve the most accurate predictions compared to baseline models. The transfer learning strategy enables the models to learn general brain dynamics from large amounts of simulated impacts and then adapt to specific target impacts.

DECLARATION OF CONFLICT OF INTERESTS

The authors declare no conflict of interests.

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