Deep Learning methods applied to the assessment of Brain Injury Risk

Nicolas Bourdet, Caroline Deck, Arnaud Trog, Frank Meyer, Vincent Noblet, Rémy Willinger

Abstract It is well known that model-based brain injury criteria present higher potential to predict injury than global head kinematic parameters. Numerical head injury prediction tools are time consuming and require FE-skilled users. To address these difficulties, we suggest applying deep learning techniques to an existing brain FE model. A total of 3,754 head impacts coming from experimental helmet testing were considered as input for the analysis. Each input was expressed in terms of three linear accelerations and three angular velocities versus time, when the target metric was the maximum Von Mises Stress (VMS) computed within the brain via the FE analysis.

The architecture used for the Deep Learning Model (DLM) was the U-Net. The dataset was split into three datasets dedicated for learning and testing. The quality of the DLM was assessed via the Maximum Absolute Error between FEM- and DLM-computed brain maximum VMS. Further, a regression analysis of brain response and injury risk estimated with both methods was conducted. Results showed that the learning process of the network worked adequately and that deep learning techniques were applicable to predict brain response, without any FE analysis, in a realistic way by considering the 6D head kinematic vs time.

Keywords Deep Learning, U-Net architecture, Brain injury, Von Mises Stress.

I. INTRODUCTION

The evaluation and optimization of head protection systems in both automotive and helmet industries require human head surrogates and adequate head injury prediction metrics. Since the 1970s, dummy heads and headforms have been used for these purposes, associated to their linear acceleration via the maximum value or the Head Injury Criteria (HIC). As it is well accepted since Holbourn (1945) [1] that the visco-elastic brain material is extremely sensitive to head rotational loading, Takhounts et al. (2013) [2] suggested Brain Injury Criteria (BrIC) metric, followed by Universal Brain Injury Criteria (UBric) metric [3] and, more recently, DAMAGE metric [4], among others. In order to consider tissue-level brain injury criteria that take into account the six dimensions time evolution of a complex head loading as well as the complex brain geometry and time dependent constitutive law, model-based brain injury criteria have been developed and applied in research as well as in industrial context.

Among them, KTH [5], THUMS [6], WSU [7, 8], DHIM [9], GHBMC [10] and SUFEHM [11] FE head models are known to be extensively used for the simulation of road accidents and sport accidents in order to derive model-based brain injury criteria. Even if these kinds of criteria are still open to debate and harmonization efforts, the so-called “experimental versus numerical” test method is increasingly applied. This approach consists by considering the experimental 6D time evolution of the dummy head or headform kinematic as the input of the head impact FE simulation by applying the head kinematic field to the skull considered as non-deformable for a given range of impacts. This method has been applied to the assessment of bike helmets [12, 13], hockey helmets [14], motorcycle helmets [15] and equestrian helmets [16]. Since 2018 it has also been considered for the monitoring of brain injury risk within Euro NCAP [17].

It is well known and accepted that Head FE Models may give access to tissue-level injury metrics when Anthropomorphic Test Devices (ATD) lead to more global head kinematic parameters in an experimental framework. On the other hand, numerical tools are time consuming and require skilled staff for analysis and exploitation of results. Three solutions are known to address these difficulties: the development of dedicated HBM post-processors; the pre-computation of a high number of similar impact pulses; and the application of Deep Learning Methods.

N. Bourdet (e-mail: nicolas.bourdet@unistra.fr), C. Deck and F. Meyer are Ph.D researchers in Biomechanics(MMB/MechaniCS) at ICube UMR 7357 University of Strasbourg. A. Trog and V. Noblet are engineers in the fields of deep learning (IMAGES/IRIS) ICube UMR 7357 University of Strasbourg.

An automatic head simulation post-processor was suggested by Strasbourg University [18] where the "Injury Risk Assessment Tool" reads the maximum intra-cerebral Von Mises Stress (VMS) and expresses the injury risk via the dedicated injury risk curve. More recently, this method was implemented in the so-called Dynasaur program [19] where a similar approach was applied to the full HBM. The pre-computation of a high number of head impact pulses in order to predict brain response without any head FE modelling was suggested by Ji *et al.* in 2015 [20]. This study investigated the feasibility of pre-computed brain response atlas to estimate the brain strains using isolated parametrized rotational acceleration impulses. The method was successively evaluated against responses simulating two real-world head rotational pulses. It was concluded that this method could be developed in order to progress towards real-time estimation of tissue-level brain injury metrics. Deep Learning techniques were applied by Liang et al. (2017) [21] to predict stress distribution in order to provide an accurate and fast surrogate for FE analysis. The authors applied a Deep Neural Networks method for the prediction of stress in an aorta FEM and the efficiency of the method for a real-time estimation of organ responses was demonstrated. More recently, Zhan et al. (2020) [22] published a deep learning head model for real-time estimation of entire brain deformation under concussion. A total of 1,803 head impacts from American Football incidents were used for the development of the strain prediction algorithm in each element of the brain model. A Deep Neuronal Network was used to act as a function approximator to learn the relationship between the input kinematic and the calculated MPS from FE simulation. It was concluded that the method remarkably accelerated the calculation process compared with conventional FE simulation. Moreover, it was shown that the deep learning was accurate in predicting the level of brain MPS as well as the specific region of the brain suffering from the highest strain. Interestingly Wu et al. (2019) [23] developed a convolution neutral network (CNN) to estimate regional brain strain in real time by considering head rotational velocity profiles as 2D images along the three reference axes for input. Several brain strain metrics were considered and based on 2592 input pulses it was shown that the MPS for the whole brain was accurately estimated with a R^2 value of 0.996. Similarly Ghazi et al. (2021) [24] applied the CNN model to instantly estimate element-wise distribution of MPS of the entire brain by considering both, rotational velocity and acceleration 2D profiles for the three head reference axis. It was concluded that the CNN-estimated responses are accurate for 92.1% of the cases in terms of magnitude and location.

In the context of Machine Learning applied to the assessment of brain injury risk in order to speed-up modelling efforts, the present study applies deep learning techniques directly to the estimation of maximum intra-cerebral Von Mises Stress computed with an existing brain FEM that has been shown to be best correlated with the occurrence of moderate concussion [25]. A total of 3,000 experimental 6D headform kinematic responses, recorded in the context of linear and oblique helmet tests, were considered for the FE simulation of the brain response and the assessment of brain injury risk. This material was partly used during the learning process and partly for the testing of the derived deep learning algorithm, with a final objective of progressing towards a FE-model-free brain injury risk assessment tool.

II. METHODS

Brain FE model and injury metric

This study is based on Strasbourg University FE Head Model (SUFEHM) (illustrated in Fig. 1), which is a numerical model of the human head, including realistic brain and skull material laws, and which permits the computation of the mechanical brain response under impact. Validation of this head model was provided in earlier studies [25, 26], against local brain motion data [27, 28], as well as against intracranial pressure data [29, 30].

In addition to the model validation, 109 real-world head trauma cases were simulated with this head model to derive brain injury criterion in terms of intracerebral Von Mises Stress to predict moderate concussion or short coma, known as AIS2+ injuries. Based on an in-depth Binary Logistic [31, 32] analysis of different computed intracerebral parameters as well as by considering different percentiles, the Nagelkerg parameter that expresses the quality of the regression showed that maximum brain Von Mises Stress was the most appropriate metric to predict moderate concussion.

The proposed brain injury tolerance limit for a 50% risk of this reversible brain injury has been established at 37 kPa [12, 33]. The equation of the brain tolerance curve obtained with the Binary Logistic method for the computed VMS extracted from SUFEHM is recalled in Eq. (1) and plotted in Fig.1. along with the 5% and 10% error curves. As the option was chosen to consider the best mathematical fit instead of forcing at zero, this curve does not show a zero risk for zero stress.

$$Risk = \frac{1}{1 + e^{3.178 - 0.087.VMS}} \quad (1)$$

where VMS is the max. value of brain Von Mises Stress in kPa.

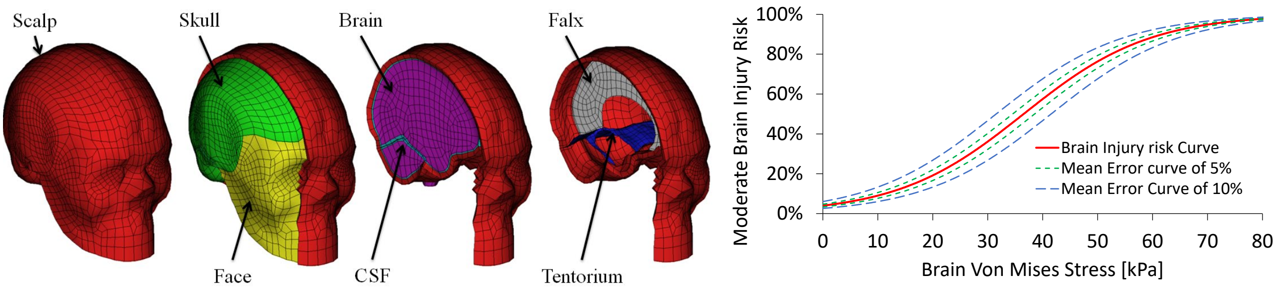


Fig. 1. Illustration of the different parts of the Head Finite Element Model and the related brain tolerance curve.

Learning and Test data sets

The data sets used were established in the context of an extensive helmet evaluation program, including bicycle [12] and motorcycle [15, 34, 35] helmets. They consist of 3,754 helmet impacts against horizontal and oblique anvils, with the recording of the 6D headform kinematic associated to the numerical simulation of all impacts with SUFEHM head model in order to compute the maximum brain VMS and to assess the brain injury risk for each of the impacts. Each input was expressed in terms of three linear accelerations and three angular velocities versus time, while the output metric was the time history of the maximum Von Mises Stress in the entire brain, computed within the brain model via the FE analysis.

The model learning and assessment processes applied in the present study are described in the workflow shown in Fig. 2. In order to develop a Deep Learning Model (DLM) that is able to predict the maximum brain VMS for a given 6D head kinematic, there is a need to define a significative and isolated data set dedicated to learning.

With all the data gathered with very different helmets and impact conditions, there was a need to distribute the whole data sets of 3,754 impacts into a training dataset (3,035 data), a validation data set (336 data) and a test data set (383 data). The data split was carried out randomly. The first step consisted in establishing the best hyper-parameters for the optimisation of the learning process by using the training and the validation data sets. In a second step, these two data sets were used to train the U-Net model [36] until the final DLM. Finally, the test data set of head impacts was used to evaluate the robustness of the proposed DLM.

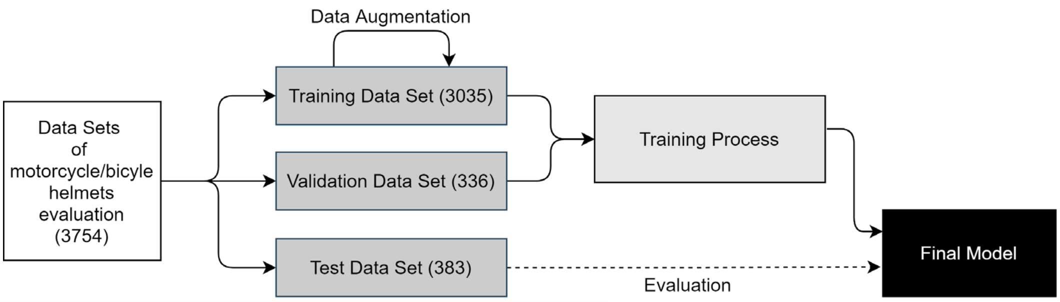


Fig. 2. Workflow of the training and testing methodology.

It is important to point out that all the datasets present a similar distribution in terms of amplitude, as shown in Fig. 3. If it is obvious that the learning data must be different from the test data, all considered head impacts are in a range of impacts as encountered in the context of helmet tests. In the present study the distributions of the learning data are around the mean value of 153 g, 24 rad/s and 32 kPa for maximum linear acceleration, angular velocity and brain Von Mises Stress respectively, as reported in Table I.

For the assessment of the performance of the DLM, the test data of 383 helmeted head impacts were considered. The peak linear acceleration and angular velocity values vary from 77 g to 308 g, with a mean value of about 152 ± 42 g and 2.7 rad/s to 56.3 rad/s with a mean value of about 24.9±10.7 rad/s, respectively. Coming to the maximum brain Von Mises Stress calculated with the SUFEHM model for each of the 383 helmeted impacts, a mean value of about 33.2 ± 12.7 kPa was calculated (9.3 kPa to 79.1 kPa) and is also reported in Table I.

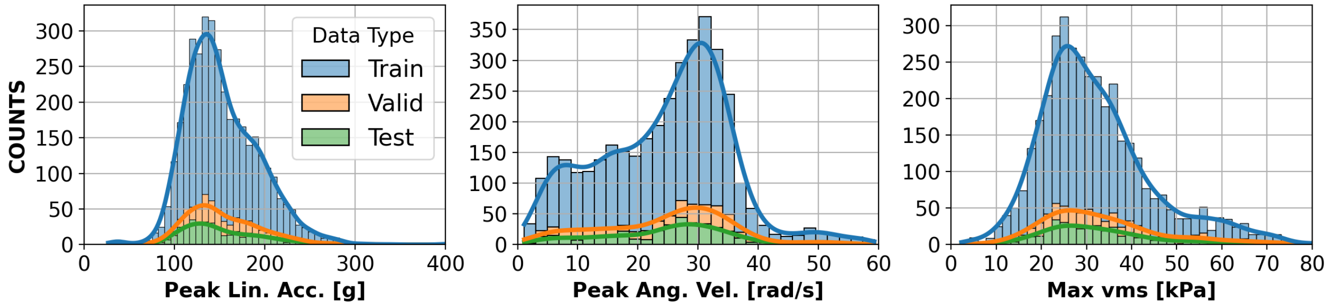


Fig. 3. Distribution of the training (Train), validation (Valid) and test (Test) data sets in terms of peak resultant linear acceleration, peak angular velocity and maximum of VMS calculated with brain FEM.

TABLE I
DISTRIBUTION OF THE LEARNING DATA SET (3,754 CASES) IN TERMS OF MEAN VALUES

Data Sets	Counts	Lin. Acc. [g]	Ang. Vel. [rad/s]	Max VMS [kPa]	Brain Injury Risk AIS2+
Train	3,035	153 ± 41	24.5 ± 10.8	31.9 ± 12.4	41% ± 21%
Valid	336	155 ± 37	24.1 ± 10.9	33.3 ± 13.3	43% ± 23%
Test	383	152 ± 42	24.9 ± 10.7	33.2 ± 12.7	43% ± 22%
All	3,754	153 ± 40	24.5 ± 10.8	32.2 ± 12.6	41% ± 22%

Deep Learning Model

The U-Net model applied in this study is a convolutional neural network originally introduced for biomedical image segmentation by [36]. Just as for image, each different kernel computes a different representation of the input. Therefore, the goal is to find/learn the best set of kernels to have a meaningful lower representation of the input to predict the output. This model has two symmetrical parts, an encoder part and a decoder part, as illustrated in Fig. 4. The encoder, on the left side, will learn features from the input that will be passed to the decoder, on the right side, to predict the output. To apply this method, we thus first reduced the dimension of the time series into features learned by the network, which allows us to predict the output as closely as possible to the FE-computed result.

The encoder takes all input signals as input, applies a convolutional block and a MaxPooling of size 2 (max pool) to do down sampling and repeat this procedure 4 times. The convolutional blocks are defined as the repetition of two convolution of size 3 (conv) followed by a batch normalization (BN) which maintains the mean output close to 0 and the output standard deviation close to 1, as well as a nonlinear activation function (Relu). The decoder first operates a transpose convolution (up-conv) of the learned features which are then concatenated (concat) with features from the corresponding level of the encoder and then apply a convolutional block.

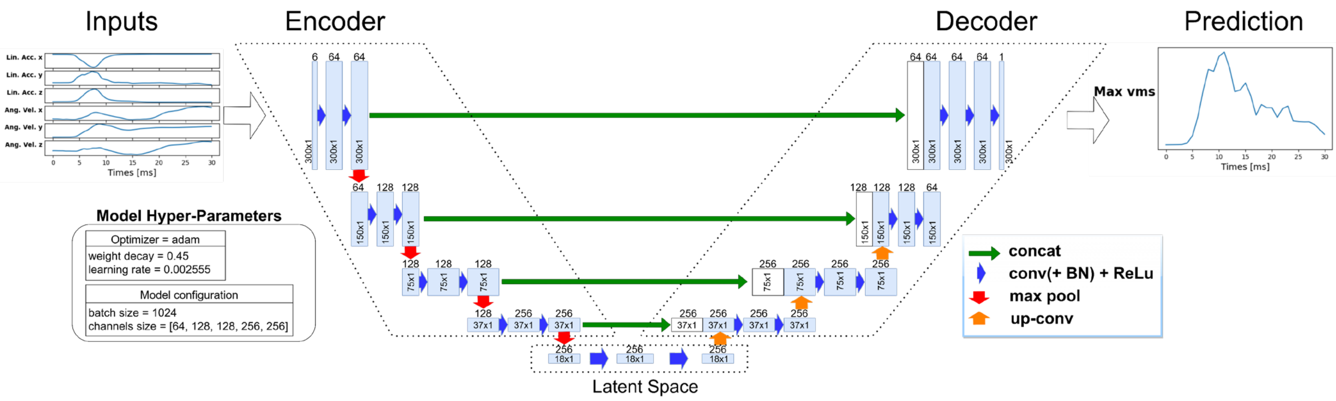


Fig. 4. U-Net architecture used to approximate SUFEHM brain response in terms of VMS.

Since the performance of the model strongly depends on the hyper-parameters like the channels size, the batch size, the learning rate as well as the weight decay of the optimizer, a Bayesian optimization was used to tune them and are reported in Fig. 4.

The optimization process of the U-Net model aims to minimize the loss function defined by $f(vms, \widehat{vms}) = log\big(cosh(vms - \widehat{vms})\big)$, where $vms, \widehat{vms}$ are the maximum Von Mises Stress (VMS) vs time evolution calculated with FE and estimated by the U-Net model, respectively. The time evolution of maximum-VMS was discretized into 300 steps, i.e. with a timestep of 0.1 ms. The other metric used to evaluate the model during the optimization process was the Mean Absolute Error metric (MAE_{valid}) on the maximum VMS versus time on the validation data set of 336 data and is defined by Eq. (2). Thus, the loss function as well as MAE_{valid} compare the entire time evolution of the maximum VMS at each epoch.

$$MAE_{valid} = \frac{1}{336}\sum_{i=1}^{336}\left(\frac{1}{300}\sum_{t=1}^{300}\left|VMS_i^t - \widehat{VMS_i^t}\right|\right) \tag{2}$$

With VMS_i^t represents the Von Mises Stress at the time t for the i data result.

As the brain injury risk is evaluated by using the maximum VMS of the maximum VMS vs time, the performance of the U-Net model was estimated by calculating the Mean Absolute Error metric (MAE_{test}) on the maximum VMS for each of the 383 test data as defined by Eq. (3) and Eq. (4) in terms of VMS and Risk:

$$VMS\ MAE_{test} = \frac{1}{383}\sum_{i=1}^{383}\left|VMS_i^{max} - \widehat{VMS_i^{max}}\right| \tag{3}$$

With $VMS_i^{max} = max_{t\epsilon[0,300]}(VMS_i^t)$ and $\widehat{VMS_i^{max}} = max_{t\epsilon[0,300]}\big(\widehat{VMS_i^t}\big)$

$$Risk\ MAE_{test} = \frac{1}{383}\sum_{i=1}^{383}\left|Risk_i - \widehat{Risk_i}\right| \tag{4}$$

With $Risk_i = \frac{1}{1+e^{\left(3.178-0.087.VMS_i^{max}\right)}}$ and $\widehat{Risk_i} = \frac{1}{1+e^{\left(3.178-0.087.\widehat{VMS_i^{max}}\right)}}$

In addition, statistical metrics, such as Pearson’s correlation coefficient, and accuracy analysis, by calculating the proportion of cases whose max VMS Error was less than a threshold value (2 kPa and 5 kPa) as defined in Eq. (3) and Eq. (4), were calculated. These two thresholds correspond to a 5% and 10 % mean error on the brain injury risk, as illustrated in Fig. 1.

$$Max\ VMS\ Error_i\ =\ \left|VMS_i VMS_i^{max} - VMS_i\widehat{VMS_i^{max}}\right| \tag{3}$$

$$P(Max\ VMS\ Error_i \leq X) = Proportion\ of\ cases\ whose\ \max VMS\ error\ is\ less\ than\ X \\ with\ X = 2\ kPa\ and\ 5\ kPa \tag{4}$$

III. RESULTS

The U-Net model was trained for 500 iterations with a simple hold-out validation. For each epoch, a batch size of 1,024 was used. Fig. 5 represents the loss functions on training and validation data sets as well as the corresponding MAE values on validation data set as a function of epochs. Table II reports the mean MAE values calculated on the validation data with the best model and shows a mean MAE of 0.96 ± 1.09 kPa in terms of maximum VMS.

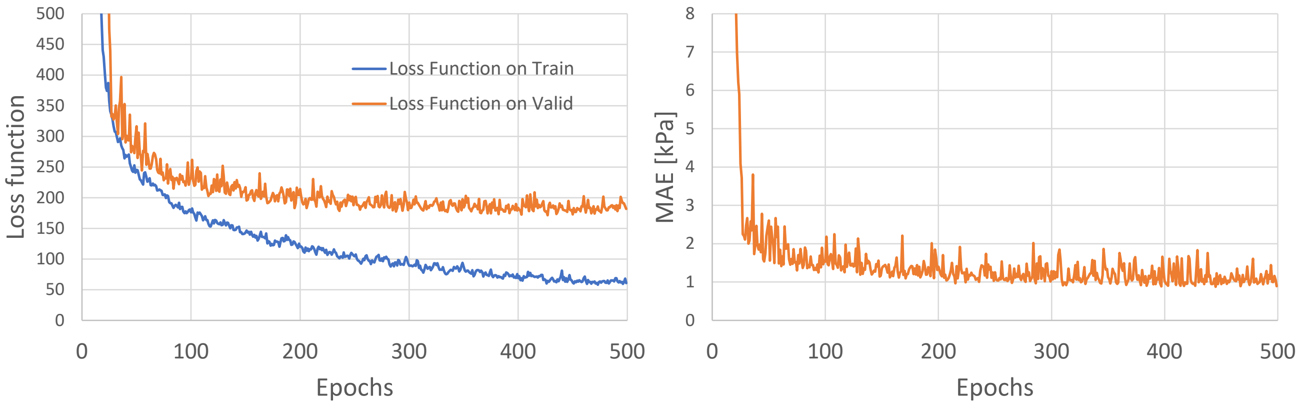


Fig. 5. Evolution of the loss functions on train and valid data sets and MAE values on valid data set.

TABLE II
MAE VALUES AND STANDARD DEVIATION CALCULATED FOR THE PROPOSED MODEL IN TERMS OF MAX VMS AND RISK ON THE VALID DATA SET FOR THE BEST MODEL OBTAINED

Metrics	**MAE ± Std**
Max VMS [kPa]	0.96 ± 1.09
Risk [%]	2.97 ± 3.52

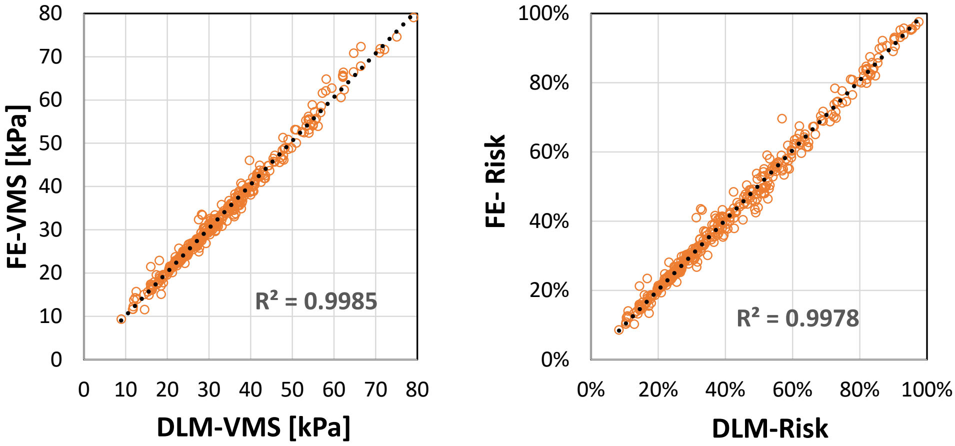
After the training process, the assessment of the performance of the U-Net model was carried out by using the test data set. The MAEs were then computed and are reported in Table III in terms of max. VMS and in terms of brain injury risk.

The MAE calculated from training data sets in terms of VMS is similar to that calculated on the test data set with a value of 0.96 kPa.

Further, the correlation between the maximum brain VMS calculated with the Deep Learning Model (DLM-VMS) and the maximum VMS computed with the head FEM (FE-VMS) leads to a Pearson's correlation coefficient equal to 0.9985. The accuracy and the robustness of the DLM can be illustrated by calculating the proportion of cases whose absolute error of the max. VMS was less than 2 kPa and 5 kPa, which are 96.3% and 99.5% respectively. In a similar way, the metrics are calculated for the brain injury risk, with values reported in Table III. Finally, linear regressions between maximum Von Mises Stress calculated with DLM-VMS and computed with FE-VMS, as well as in terms of brain injury risk DLM/FE, are reported in Fig. 6.

TABLE III
STATISTIC METRICS CALCULATED WITH TESTS DATA SET (383 CASES) IN TERMS OF MAX VMS AND RISK

Metrics		**Values**
Max VMS Mean Absolute Error (MAE_{test}) [kPa]		0.96 ± 1.09
Risk Mean Absolute Error (MAE_{test}) [%]		1.5% ± 1.7 %
R^2 Pearson Correlation between DLM-VMS and FE-VMS		0.9985
R^2 Pearson Correlation between DLM-Risk and FE-Risk		0.9978
Accuracy on proportion of cases with Max VMS absolute error	***< 2 kPa***	96.3%
	< 5 kPa	99.5%



(a) (b)

Fig. 6. (a) Linear regression between maximum Von Mises Stress calculated with the Deep Learning Model (DLM-VMS) and computed with the brain FE model (FE-VMS). (b) Linear regression between the Risk obtained by the DLM-VMS (DLM-Risk) and by the FE-VMS (FE-Risk) using Eq. (1).

The assessment of the DLM is further illustrated in Fig. 7, with the representation of the distribution in terms of boxplot, without outliers, of the error between the max. VMS values computed by the FE model and the DLM model according to the range of brain injury risk. It can be observed that error dispersion on max. VMS is around 4.4 kPa, with a maximal error dispersion in the highest risk range (90–100%). This observation is because the training data set considered in this study has a Gaussian distribution around a VMS of 32 kPa, i.e. a risk of about 40%.

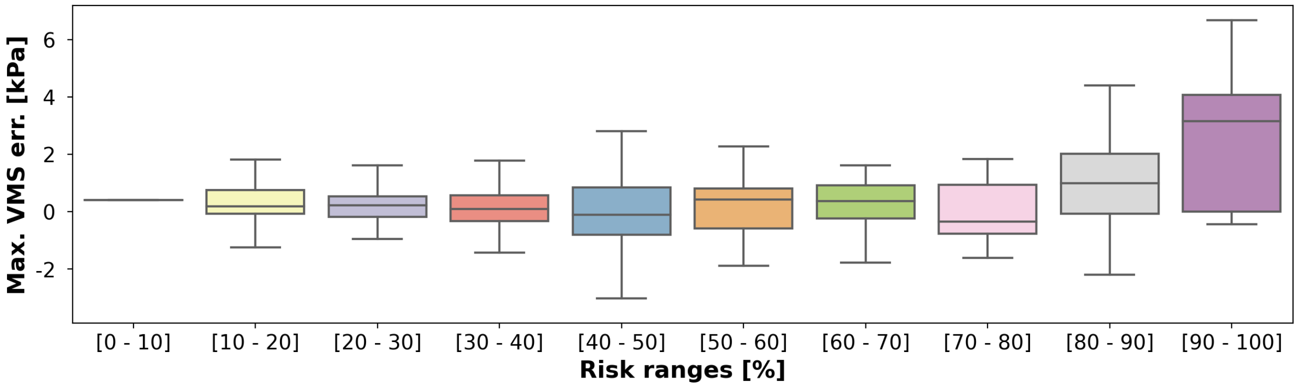


Fig. 7. Distribution of the Max VMS error in terms of boxplot according to the Risk ranges.

IV. Discussion

In this study a Deep Learning Model (DLM) was developed in order to predict maximum brain VMS for a given 6D head kinematics without the use of any brain FEM. For the training, validation and testing of the DLM, a dataset of 3,754 experimental head kinematics, recorded during an extensive helmet evaluation program, as well as the brain response computed with an existing brain FEM was used. Results show that the Maximum Absolute Errors between the maximum brain VMS estimated with the DLM and the FE-computed values are in an acceptable range. Moreover, the regression between the DLM-VMS and the FE-VMS shows very high correlation, demonstrating that the deep learning approach holds potential for the future. Very high correlation between FE-computed brain response of American Football incidences and real time estimation of the brain response via a convolution neutral network (CNN) were established also by Wu et al. (2019) [23] and Ghazi et al. (2021) [24]. These recent studies focussed on regional brain strain and showed that MPS whole brain was better correlated than other strain metrics such as MPS corpus calosum or Fiber Strain corpus calosum. Strain and stress are linked via the brain constitutive law and due to the complex visco-elastic characteristics of brain, so its time dependence, there is no strait forwards link between MPS and VMS. Moreover, a number of FE based brain injury metrics [5–7, 9, 37] as well as Global metrics [2–4] consider MPS as injury metric when Deck et al.2008 [21] focusses on VMS. It would therefore be of interest to extend the present study to the computation of MPS and to establish the correlation between FE-computed MPS with DLM_MPS. A further difference between the present study and [23, 24], is that these earlier approaches consider two-dimensional head rotational velocity and/or acceleration profiles for the three head reference axes, when the present study suggest to implement both, the linear and the rotational kinematic into the FE and Deep Learning Models. If it is well established that the rotational loading of the head is a key parameter leading to potential brain injury, the linear head acceleration should not be excluded, to the present author's opinion. Probably it is worth in this discussion to keep in mind that [23, 24] focuses on American Football-related pulses when the present study considers oblique and linear helmet tests. If the first are mainly rotational loading, the second clearly show high linear accelerations. It must be stated also here that if brain MPS is mainly sensitive to rotational loading it is potentially less sensitive to the linear loading then VMS is, as observed in [38]. This debate however needs further in-deep investigation focussing on a same brain FEM.

When considering the Deep Learning aspects of the present study, U-Net structure is a fully convolutional neural network composed of an encoder which compresses the data, a latent space which gather the compressed data and a decoder which extrapolates the output by using the latent space and the encoder part. This structure allows to contribute consistently to the accuracy compared to a simple convolutional neural network. The training time is much more important due to the huge number of parameters, and it would be of interest to compare them with CNN-based models. However, in the context of the present study the learning phase is conducted only once in order to build-up the brain injury prediction tool, so the learning time is not of key importance.

Another limitation is that the DLM needs "further learning". It must be stated here that so far, the learning of the model was concentrated on impact conditions directly linked to the helmet evaluation program, i.e. Frontal, Lateral and Occipital impacts against a horizontal anvil followed by three impacts against a 45° inclined anvil leading to head rotation around the three reference axes. Consequently, head impact pulses ranged within 5 to 15 ms in duration, 77 to 308 g in linear acceleration and 3 to 56 rad/s in angular velocity, leading to a Gaussian distribution of VMS around 32 kPa. This comment is well illustrated by Fig. 7 where it appears that the lowest errors are for the VMS of 11 to 46 kPa, i.e. for injury risk of 10% to 70% and that this errors increases with higher injury risk. Therefore, it is important to mention that for the use of the DLM under very different impact conditions the model must be trained in a larger range of impact conditions. This kind of limitation was also pointed by [23] when expressing that the trained CNN permits instantly estimated regional brain strains with sufficient accuracy, especially for within-range impacts and that the temporal "shapes" of the head rotational velocity profiles were limited to what the measured/reconstructed impact datasets offered. There is also a limitation about potential skull deformation as the proposed approach is based on 6D non-deformable skull accelerations. Therefore, the developed DLM is restricted to use for protected impacts, such as helmeted head or head of car occupant, for which it is reasonable to consider the skull as a rigid body and to consider the 6D head kinematic as the input of the simulation of the head impact. However, in the case of direct head impact against a rigid structure or under ballistic loading, the "experimental vs numerical" approach considered in this paper is no longer applicable, so the present DLM is not. In such cases, it is necessary to simulate the head-structure interaction with a deformable skull model associated to skull fracture criteria [39].

A further limitation in the training process is the use of a simple hold-out validation. The use of k-fold cross validation is useful when the performance of the model varies significantly depending on the partitioning chosen between the training set and the test set. As the different datasets were obtained randomly, no significative difference was observed in the present study.

Finally, the limitations of the proposed DLM model are also linked to the limitation of the brain FE model and related brain injury criteria used. In this field a number of ongoing research projects must be mentioned, demonstrating that the brain model applied is a simplified model that can be replaced by more advanced brain models in the future. Among them, it is probably the brain constitutive law supposed to be linear viscoelastic in this study that must be improved in order to implement hyper-viscoelastic and anisotropic brain constitutive laws which enable it to compute the maximum axonal strains as reported in recent literature [40–43].

V. CONCLUSIONS

The assessment of brain injury risk based on tissue-level brain injury criteria typically requires the FE computation of the impact with a brain FEM as well as a dedicated tolerance curve. In this study a Deep Learning Model (DLM) was developed in order to predict maximum brain VMS for a given 6D head kinematics without the use of any brain FEM and to assess the brain injury risk accordingly. The dataset used for the learning process and the testing of the DLM involved 3,754 experimental head kinematics recorded during helmet impact tests, associated to the brain response computed with an existing brain FEM. Therefore, in the present study, head impact pulses ranged within 5 to 15 ms in duration , 77 to 308 g in linear acceleration and 3 to 56 rad/s in angular velocity   Results show that the Maximum Absolute Error between the maximum brain VMS estimated with the DLM, on the one hand, and with the FE-computed VMS value, on the other, is in an acceptable range as the regression between the DLM-VMS and the FE-VMS shows very high correlation, demonstrating that the deep learning approach should be further developed for research and industrial applications. The results demonstrate that deep learning methods can be applied in the context of brain response estimation without any FE computation, which will be of very high interest to the industrial sphere. As a whole, the learning process of the network worked adequately by learning from its mistakes through minimizing a cost function. However, this process must be extended to a larger range of head impact condition, such as extremely short or much longer pulses, before general application of the tool outside the helmet evaluation domain. In other words, the model needs to learn more.

VI. REFERENCES

[1] Holbourn A. H. S., (1945), The mechanics of brain injuries, *British Medical Bulletin*, 3, (6): pp. 147-149, URL: https://doi.org/10.1093/oxfordjournals.bmb.a071895.

[2] Takhounts E. G., Craig M. J., Moorhouse K., McFadden J., Hasija V., (2013), Development of brain injury criteria (BrIC)., *Stapp car crash journal*, 57, (November): pp. 243-266.

[3] Gabler L. F., Crandall J. R., Panzer M. B., (2018), Development of a Metric for Predicting Brain Strain Responses Using Head Kinematics, *Annals of Biomedical Engineering*, 46, (7): pp. 972-985, doi: 10.1007/s10439-018-2015-9.

[4] Gabler L. F., Crandall J. R., Panzer M. B., (2019), Development of a Second-Order System for Rapid Estimation of Maximum Brain Strain, *Annals of Biomedical Engineering*, 47, (9): pp. 1971-1981, doi: 10.1007/s10439-018-02179-9.

[5] Kleiven S., (2007), Predictors for traumatic brain injuries evaluated through accident reconstructions., *Stapp car crash journal*, 51, (October): pp. 81-114.

[6] Kimpara H., Iwamoto M., (2012), Mild traumatic brain injury predictors based on angular accelerations during impacts, *Annals of Biomedical Engineering*, 40, (1): pp. 114-126, doi: 10.1007/s10439-011-0414-2.

[7] Viano D. C., Casson I. R., et al., (2005), Concussion in professional football: brain responses by finite element analysis: part 9, *Neurosurgery*, 57, (5): pp. 891-916, doi: 10.1227/01.neu.0000186950.54075.3b.

[8] Zhang L., Yang K. H., King A. I., (2001), Comparison of brain responses between frontal and lateral impacts by finite element modeling, *Journal of Neurotrauma*, 18, (1): pp. 21-30, URL: http://www.ncbi.nlm.nih.gov/pubmed/11200247.

[9] Ji S., Zhao W., Li Z., McAllister T. W., (2014), Head impact accelerations for brain strain-related responses in contact sports: a model-based investigation, *Biomechanics and Modeling in Mechanobiology*, 13, (5): pp. 1121-1136, doi: 10.1007/s10237-014-0562-z.

[10] Mao H., Zhang L., et al., (2013), Development of a Finite Element Human Head Model Partially Validated With Thirty Five Experimental Cases, *Journal of Biomechanical Engineering*, 135, (11): pp. 111002, URL: https://asmedigitalcollection.asme.org/biomechanical/article/135/11/111002/370929/Development-of-a-Finite-Element-Human-Head-Model.

[11] Sahoo D., Deck C., Willinger R., (2015), Axonal Strain as Brain Injury Predictor Based on Real-World Head Trauma Simulations., *IRCOBI Conference Proceedings*, pp. 186-197, URL: europ.

[12] Deck C., Bourdet N., Meyer F., Willinger R., (2019), Protection performance of bicycle helmets, *Journal of Safety Research*, 71: pp. 67-77, URL: https://linkinghub.elsevier.com/retrieve/pii/S0022437519306176.

[13] Bliven E., Rouhier A., et al., (2019), Evaluation of a novel bicycle helmet concept in oblique impact testing, *Accident Analysis & Prevention*, 124: pp. 58-65, URL: http://www.sciencedirect.com/science/article/pii/S0001457518303713.

[14] Post A., Kendall M., et al., (2018), Brain tissue analysis of impacts to American football helmets, *Computer Methods in Biomechanics and Biomedical Engineering*, 21, (3): pp. 264-277, doi: 10.1080/10255842.2018.1445229.

[15] Bourdet N., Deck C., Meyer F., Willinger R., (2019), Experimental and numerical considerations of helmet evaluation under oblique impact, *Journal of Transportation Safety & Security*, pp. 1-14, doi: 10.1080/19439962.2019.1630695.

[16] Bourdet N., Deck C., Meyer F., Willinger R., (2020), A new comparative testing method for equestrian helmets, *International Journal of Crashworthiness*, pp. 1-10, URL: https://www.tandfonline.com/doi/full/10.1080/13588265.2020.1859758.

[17] (2020), European New Car Assesment Program: MPDB Frontal Impact Testing, .

[18] Deck C., Willinger R., (2008), APROSYS - Numerical evaluation of the helmet prototype against improved head injury criteria, .

[19] Martin Schachner, Jakub Micorek, et al., Dynasaur / Vehicle Safety Institute TU Graz, *https://gitlab.com/VSI-TUGraz/Dynasaur*, , URL: https://gitlab.com/VSI-TUGraz/Dynasaur.

[20] Ji S., Zhao W., (2015), A Pre-computed Brain Response Atlas for Instantaneous Strain Estimation in Contact Sports, *Annals of Biomedical Engineering*, 43, (8): pp. 1877-1895, doi: 10.1007/s10439-014-1193-3.

[21] Liang L., Liu M., Martin C., Sun W., (2018), A deep learning approach to estimate stress distribution: a fast and accurate surrogate of finite-element analysis, *Journal of The Royal Society Interface*, 15, (138): pp. 20170844, doi: 10.1098/rsif.2017.0844.

[22] Zhan X., Liu Y., et al., (2020), Deep Learning Head Model for Real-time Estimation of Entire Brain Deformation in Concussion, pp. 1-12.

[23] Wu S., Zhao W., Ghazi K., Ji S., (2019), Convolutional neural network for efficient estimation of regional brain strains, *Scientific Reports*, 9, (1): Art. nº pp. 1, URL: https://www.nature.com/articles/s41598-019-53551-1.

[24] Ghazi K., Wu S., Zhao W., Ji S., (2021), Instantaneous Whole-Brain Strain Estimation in Dynamic Head Impact, *Journal of Neurotrauma*, 38, (8): pp. 1023-1035, doi: 10.1089/neu.2020.7281.

[25] Deck C., Willinger R., (2008), Improved head injury criteria based on head FE model, *International Journal of Crashworthiness*, 13, (6): pp. 667-678, doi: 10.1080/13588260802411523.

[26] Deck C., Willinger R., (2009), The current state of the human head finite element modelling, *International Journal of Vehicle Safety*, 4, (2): pp. 85-112, URL: http://www.inderscience.com/search/index.php?action=record&rec_id=28921&prevQuery=&ps=10&m=or.

[27] Hardy W. N., Foster C. D., et al., (2001), Investigation of Head Injury Mechanisms Using Neutral Density Technology and High-Speed Biplanar X-ray, *Stapp Car Crash Journal*, 45: pp. 337-368.

[28] Hardy W. N., Mason M. J., et al., (2007), A Study of the Response of the Human Cadaver Head to Impact, *Stapp car crash journal*, 51: pp. 17-80, URL: http://www.ncbi.nlm.nih.gov/pmc/articles/PMC2474809/.

[29] Nahum A. M., Smith R., Ward C. C., (1977), Intracranial Pressure Dynamics During Head Impact, , URL: http://papers.sae.org/770922/.

[30] Trosseille X., Tarriére C., Lavaste F., Guillon F., Domont A., (1992), Development of a F.E.M. of the Human Head According to a Specific Test Protocol, , URL: http://papers.sae.org/922527/.

[31] Hosmer D. W., Lemesbow S., (1980), Goodness of fit tests for the multiple logistic regression model, *Communications in Statistics - Theory and Methods*, 9, (10): pp. 1043-1069, URL: https://www.tandfonline.com/doi/abs/10.1080/03610928008827941.

[32] David W. Hosmer, Stanley Lemeshow., (2000), *Applied Logistic Regression, 3rd Edition | Wiley*, .

[33] Caroline Deck, Rémy Willinger., (2009), Head injury prediction tool for protective systems optimisation, *7th European LS-DYNA Conference*, pp. 11.

[34] Bourdet N., Deck C., Willinger R., (2017), Coupled experimental versus numerical helmet evaluation under multidirectional impact, 103: , URL: https://figshare.com/articles/Coupled_experimental_versus_numerical_helmet_evaluation_under_multidirectional_impact/5405230.

[35] Bourdet N., Mojumder S., et al., (2016), Proposal of a new motorcycle helmet test method for tangential impact, *IRCOBI Conference*, (IRC-16-65): pp. 12, URL: https://trid.trb.org/view/1426477.

[36] Ronneberger O., Fischer P., Brox T., (2015), U-Net: Convolutional Networks for Biomedical Image Segmentation, *arXiv:1505.04597 [cs]*, , URL: http://arxiv.org/abs/1505.04597.

[37] Sahoo D., Deck C., Willinger R., (2015), Axonal strain as brain injury predictor based on real-world head trauma simulations, *2015 IRCOBI Conference Proceedings - International Research Council on the Biomechanics of Injury*, pp. 186-197.

[38] Deck C., Bourdet N., Halldin P., DeBruyne G., Willinger R., (2017), Protection Capability of Bicycle Helmets Under Oblique Impact Assessed with Two Separate Brain FE Models, *IRCOBI Conference Proceedings*, .

[39] Sahoo D., Deck C., Yoganandan N., Willinger R., (2016), Development of skull fracture criterion based on real-world head trauma simulations using finite element head model, *Journal of the Mechanical Behavior of Biomedical Materials*, 57: pp. 24-41, doi: 10.1016/j.jmbbm.2015.11.014.

[40] Sahoo D., Deck C., Willinger R., (2016), Brain injury tolerance limit based on computation of axonal strain, *Accident Analysis & Prevention*, 92: pp. 53-70, URL: http://www.sciencedirect.com/science/article/pii/S0001457516300847.

[41] Giordano C., Kleiven S., (2014), Evaluation of axonal strain as a predictor for mild traumatic brain injuries using finite element modeling, *Stapp car crash journal*, 58: pp. 29, URL: http://search.proquest.com/openview/e6bfe8dc4c863ff93ec0f6e48e17e6b9/1?pq-origsite=gscholar&cbl=29197.

[42] Zhao W., Ji S., (2018), White Matter Anisotropy for Impact Simulation and Response Sampling in Traumatic Brain Injury, *Journal of Neurotrauma*, 36, (2): pp. 250-263, URL: https://www.liebertpub.com/doi/10.1089/neu.2018.5634.

[43] Wu T., Alshareef A., Giudice J. S., Panzer M. B., (2019), Explicit Modeling of White Matter Axonal Fiber Tracts in a Finite Element Brain Model, *Annals of Biomedical Engineering*, 47, (9): pp. 1908-1922, URL: https://doi.org/10.1007/s10439-019-02239-8.