BHBT Impactor Classification Using Machine Learning

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Abstract. A novel approach to improve injury risk assessment of behind-helmet blunt trauma (BHBT) events using machine learning is presented. Four rigid impactor profiles were fired at the ballistic load sensing headform (BLSH) using an air cannon to represent BHBT loading conditions. 14 key features were extracted from the seven-load cell array time histories recorded by the BLSH. No clear pattern emerged from the key features to easily identify which impactor corresponded to which test, therefore, a machine learning approach was used. The support vector machine (SVM) multinomial classifier was trained on a total of 48 shots, including combinations of four impactor face profiles, two test velocities, and three repeats at each of the two impact locations were provided as training/validation data. Cross-feature scaling was performed to prevent over- or under-fitting to specific features. The SVM accuracy was evaluated using stratified 12-fold cross-validation (leave-one-out cross-validation), where the model was found to have approximately 94% accuracy. Ballistic testing was then performed on infantry helmets mounted on the BLSH using 9mm FMJ and 64-grain FSP projectiles. The same 14 key features used to train the SVM on air cannon data were extracted from each ballistic event and fed into the model which predicted the equivalent impact profile. Equivalent testing was repeated on a clay-filled ballistic helmet to ascertain the actual deformation profile using the witness material which could then be compared against the profile predicted by the classifier. Finally, the predicted profiles and measured peak forces of the helmet testing were combined with the Allanson-Bailey BHBT injury risk curves to ascertain the probability of an AIS2+ injury for each event.

1. BACKGROUND

Combat helmets provide many protective benefits to the head including, in part, attenuation of blunt force impacts, resistance to penetration from ballistic projectiles and mitigation of behind-helmet blunt trauma (BHBT) from defeated projectile strikes. If not managed adequately, injuries to the head can occur and will vary with the helmet design, threat severity and human tolerance.

BHBT involves the transmission of forces from a defeated projectile strike resulting in local shell deformations and attenuation of the projectile's energy. The stiffness and strength of the shell, the amount of standoff from the head, and the use of impact liners can greatly affect the loads and resulting injury outcomes. For example, in the study of ballistic plate and ballistic helmet impacts, it was found that increasing the helmet stand-off or inserting an impact liner reduced intra-cranial pressures and skull fracture severity significantly during ballistic shell deformation [1], [2]. Additionally, helmets that exhibited larger shell deformations had greater contact areas with increased intra-cranial pressures and skull fracture severity. Skull fracture tolerance also varied with skull fracture mode (simple, comminuted) and severity (depressed, displaced) with dependence on load magnitude, distribution, rate, and the energy deposited into the anatomical structure. Observations of the injury mechanisms associated with some BHBT events have been documented in previous biomechanical studies:

1. Damage to the scalp with circular lacerations at the impact site (Bass, Boggess, Bush, & al., 2003), [1].
2. Cranial fractures with linear fractures radiating from and around the point of impact with the most severe cases resulting in comminuted fractures [4], (Bass, Boggess, Bush, & al., 2003), [1],. [2], [5].
3. Dural contusions from the dura separating from the bone at the impact site (Bass, Boggess, Bush, & al., 2003).

The risk of skull fracture under BHBT conditions has been linked to peak force metrics with the findings often limited to broad generalizations due to differences in test setups, test specimen variation, threat characteristics, data analysis metrics and test methods. Recent research by Allanson-Bailey [6] suggested that the risk of skull fracture is not only dependent on the peak transmitted force but also on the force distribution. As a result, characterizing the dynamic force and distribution may increase the specificity of the fracture risk assessments thereby improving the understanding of helmet design on protection including, for example, shell stiffness, helmet-head stand-off, local deformation shape, and impact liner interactions. For a comprehensive evaluation of the dynamic forces from shell deformation, combat helmets must be evaluated as a complete system in situ and must include the ballistic shell, impact

https://doi.org/10.52202/080042-0011

liner, and retention/sizing system, as applicable. To this end, instrumented headforms have been proposed to measure peak dynamic force but have limited ability to measure spatial force distribution [7], (Trexler, et al., 2018), [9], (Voo, Improved Repeatability and Reproducibility of the Ballistic Load Sensing Headform, 2016), [11], [12]. Alternatively, the Ballistic Load Sensing Headform (BLSH) [13] was assessed to be biofidelic under BHBT conditions (based on impacts to the temporoparietal location with a 38 mm diameter, 103-gram rigid impactor at 20 m/s and 35 m/s with comparison to force-deformation and force-time histories of PMHS corridors) [14] and has seven load sensors covered with compliant skin pad at specific cranial regions to measure peak dynamic force transmission and distribution, Figure 57. While the BLSH has been shown to be repeatable and applicable for limited BHBT conditions [13], [15], it is not known whether the spatial resolution of the BLSH sensing area is sufficient to properly characterize load distribution and skull fracture risks across a wide range of behind helmet loading conditions as proposed by Allanson-Bailey.

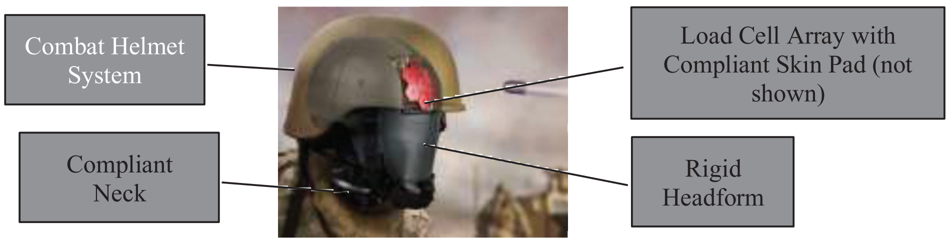


Figure 57: The Ballistic Load Sensing Headform for measuring BHBT.

The objective of the present work was to investigate whether the forces measured by the BLSH could be used to estimate the deformation profile of a helmet and, hence, skull fracture risk under the varying loading conditions defined by Allanson-Bailey. This was accomplished by comparing the measured force distribution to that obtained with direct impact to the BLSH with known projectile shapes and masses representing simulated behind-shell characteristics.

2. METHODOLOGY

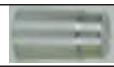
The present study proposes a method for relating the BHBT force profile (i.e., time-histories) measured using the BLSH to skull fracture risk. Published rigid impactor test data from Allanson-Bailey, include injury risk as a function of strike velocity for several impactor geometries representing typical shapes, and hence, load distribution for BHBT conditions. Therefore, a link relating BHBT test data to the various rigid impactor test conditions is required for a comprehensive injury risk assessment. The approach described herein first requires the generation of a large set of air-cannon (rigid impactor) data at different velocities and impact positions for several impactor shapes, sizes, and masses. The data is recorded using the seven-load cell array of the BLSH to generate force-time histories for the impact event across the sensing area. Next, a machine learning classifier is trained and evaluated to predict the impactor type (i.e., class) based on key features extracted from the force-time histories. Subsequently, ballistics tests are performed on helmets to quantify the BHBT force-time histories using the BLSH. Finally, data from BLSH testing is inputted into the model to classify the deformation profile as being closest to one of the impactor shapes, which is then related to injury risk curves published by Allanson-Bailey.

Rigid Impactor Testing

For the current study, four impactor shapes (Table 23) used by Allanson-Bailey in the BSM test series were selected for direct impact on the left side load cell array of the BLSH headform. The four impactors selected for testing are. The shape of the impactors used by Allanson-Bailey were partly based on that used by Raymond [14] with additional impactors of varying face curvatures and loading area, all limited to 38 mm diameter for comparison to cadaveric data of Raymond. The progression of shell shape and size as it deforms and contacts the skull was thought to be well represented by the selected impactors.

Table 23 Characteristics of four projectiles selected for direct BLSH impacts.

Projectile	Flat 38 mm	Flat 20 mm	Curved 19 mm	Curved 50 mm
Mass (g)	103.2	104.0	105.4	103.1
Diameter (mm)	38	20	38	38

Length (mm)	74	74	74	74
Surface Radius (mm)	∞	∞	19	50
Projectile				

The projectiles were launched at the BLSH using an air cannon allowing for a free flight of the projectile before impact with venting of the muzzle backpressure. Testing was conducted at 15 m/s and 25 m/s (or approximately 1.56-2.60 N·s), corresponding to similar peak force values to those expected in the ballistic testing. The shots were centred on the load cell array (hex pad #1) or offset midway between the centre and upper load cells (hex pad #1 and #7) as shown in Figure 58. Each hex pad has an approximate nominal surface area of 440 mm^2 (420 mm^2 projected). The BLSH's load cell array was positioned 20 cm from the air cannon muzzle and aligned normally to the impactor trajectory.

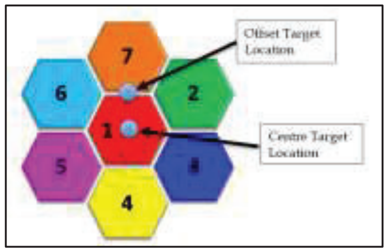


Figure 58. Targeted impact positions relative to the BLSH load cell array.

The load cell data was collected at 100 kHz using the BLSH's software with 10 kHz anti-aliasing analog hardware filters. Each channel was then digitally filtered using a phaseless Butterworth 4-pole low-pass filter with a corner frequency of 4,500 Hz, as per the BLSH's data collection protocol. The velocity of the projectile was measured at the exit of the barrel using a dual-beam IR light gate sampling at 80 MHz and triggering off the leading edge of the projectile. The BLSH skin pad covering the load cell array was inspected after every impact and was replaced when damage was observed.

BHBT testing

The air cannon tests on the BLSH aimed to develop an analysis methodology to predict the geometry of a striking impactor. The methodology could then be applied to non-perforating ballistic impacts on combat helmets to predict the resulting shell backface deformation profile. To gain insight into the shell deformations for the current study, ballistic tests were performed on the aramid combat helmets with a 9 mm 124-grain FMJ at 300 m/s (1.86 N·s) and 64-grain FSP projectiles at 400 m/s (1.66 N·s). Testing was conducted using the full shell/liner system on the BLSH to capture the loading profiles. Then, ballistic impacts to the shell with the liner removed were conducted to determine the backface deformation profile generated by the two projectiles. The 9 mm FMJ was selected to generate a flat or low curvature profile, and the 64 gr FSP was chosen to generate higher curvature profiles. To qualify the deformation profile, rigidly supported helmet shells were packed with clay (Roma Plastilina No. 1) behind the impact site, as seen in Figure 59, and were shot by the two threats. The resulting clay indentation provides a permanent record of the shell's maximum deformation and was then carefully removed from the helmet shell and cut along the mid-sagittal plane through the indentation to quantify the shape.

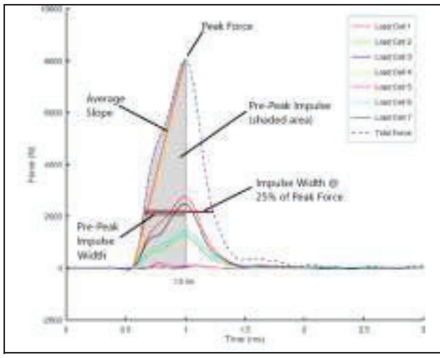
Figure 59. Helmet shell filled with clay witness material for qualification of BHBT.

Machine learning model

The problem of identifying the impactor shape based on a series of response variables is fundamentally a multinominal classification problem. For this application, Support Vector Machines (SVM) were selected due to the absence of a priori statistical information, the number of input parameters relative to the total number of points, the ability to manage multi-class supervised learning where all points have the same parameters (no missing data), and accessibility of open-source implementations. The SVM method is a supervised learning method, meaning, the correct classification must be included in the dataset for training and validation. The four classes included in the analysis were described in Table 23.

2.1.1 Feature Selection

For every test, full force-time histories were generated for the seven load cells in the array. The full data curves were not used to avoid overfitting given the limited data available. Instead, key features of each trace were extracted from the raw data for use in the SVM model. The following parameters, shown graphically and explained in Figure 60, were extracted from each event. The impact position was excluded because the classifier must distinguish the impactor profile independent of targeting accuracy and symmetries, and the velocity was excluded to not limit the model when the BHBT deformation velocity is unknown.



Peak force: Maximum sum of seven load cells.
LC Forces: Force of each load cells at time of peak force.
Loading start: First time exceeding 10 N total force.
Total loading time: From loading start to peak force
%Loading time: from X% peak force (rising) to peak force (at 10%, 25%, and 50%),
%Unloading time: from peak force (falling) to X% peak force (at 10%, 25%, and 50%),
Average slope: from impact start (10 N) to peak force,
Loading impulse: area under total load curve from loading start to peak force.
Average loading impulse: area under average slope

Figure 60. Features used in SVM training model.

2.1.1 Feature Scaling

Data for SVMs must be scaled to produce unbiased results. Typically, the scaling transforms each feature to have a minimum value of 0 and a maximum of 1. This is performed within each training group for cross-validation to prevent accidental information transfer (contamination) between groups. In most applications, parameters are independent of one another (i.e., the scaling is parameter specific). The BLSH features extracted from the time histories are not all independent. For example, a large impactor may increase the load on periphery load cells compared to a narrower impactor that only strikes a small area. This information may be lost if the parameters are scaled independently. Therefore, a scaling method which conserves the relative contribution of similar features was favoured in this application. This required scaling the parameters of a specific test using features extracted from the same test. A total of 14 parameters, shown in Table 24 were fed into the model.

Table 24 Scaling factors applied to features extracted from BLSH data.

Extracted Parameter	Scaled by	Min Scaled	Max Scaled
LC Forces (7)	Peak force	0.00	0.80
%Loading/unloading time (6)	Total loading time	0.17	1.92
Loading impulse (1)	Average loading impulse	0.68	1.29

2.1.2 Training Method

The Scikit-learn: Machine Learning in Python (version 1.2.1) was used to implement the SVM model and verification [16]. The "nu-SVC (classification)" formulation used in this analysis is an extension of SVMs that allows for multi-class problems [17]. The radial basis function kernel was used with nu set to 0.5. All other model parameters were set to the default values. Data was not augmented; rather, the load cell numbering was modified to automatically account for 12 rotational and line symmetry combinations.

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2.1.3 Evaluation and Validation

In general, supervised learning involves training a model (e.g., SVM) on a portion of the data and evaluating the model against the remaining data that was held back from training. The performance of the classifier is determined by presenting the response parameters (forces, slopes, impulses, etc.) of the test data set, and comparing the actual class (i.e., impactor shape) against the class predicted by the model. For purposes of this analysis, the accuracy will be used to assess performance as this metric describes the ability of the SVM to predict multiple classes. The accuracy is the ratio of correctly identified objects to the total count of objects. A stratified 12-fold cross-validation was used to assess accuracy. This method first divides the data into groups of equal size with the same class distribution. Here, the fold count was equivalent to leave-one-out cross-validation for a multiclass problem. Therefore, the following process was followed 12 times: 44 of the 48 shots were used to train an SVM classifier, then four shots (one of each class) were used to test the model. The expected performance of the generalized model constructed using all 48 shots is the average accuracy of the individual models.

2.1.4 Application

The SVM model described in the previous section is a trained machine-learning classifier. The model can be applied to new data to predict the impact class. In the context of the present study, data collected in BHBT helmet tests using the BLSH are processed to extract key features and fed into the SVM as inputs. The model then predicts the impactor profile based on the training data. The peak force and impactor shape can then be related to injury risk using data published by Allanson-Bailey.

3. RESULTS AND DISCUSSION

A total of 48 air cannon rigid impactor shots were performed on a bare BLSH headform. Additionally, eight ballistic tests were performed on combat helmets: two were used to establish the BHBT profile on witness clay, and the remaining six used the BLSH to record the impact force-time histories. The shots were split evenly between the 64-grain FSP and the 9 mm FMJ projectiles. The SVM classifier was trained on the air cannon data and used to predict the BHBT impact profiles to correlate each event with injury risk.

Rigid impactor testing

For every air cannon test, time series data was generated for each of the seven load cells (e.g. Figure 60), additionally, representative force distribution maps were plotted to confirm targeting accuracy (Figure 61). The 20 mm flat projectile exhibited poor accuracy and the variability in targeting was assumed to be caused by the projectile pitching or yawing (weight distribution and aerodynamic effects) upon exit of the air cannon which then led to the centre of pressure, as measured by the BLSH, not being aligned with the targeted impact location. Targeting the other three projectiles, including the 38 mm flat projectile, was accurate and repeatable. The average peak total force and strike velocities for each of the test configurations are provided in **Error! Reference source not found.**.

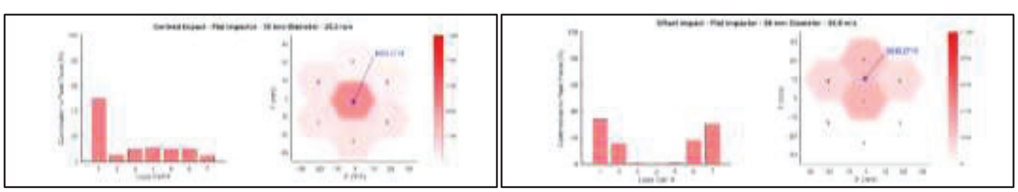

Figure 61. Representative force loading on the BLSH during air cannon testing using the 38 mm flat impactor for a centred impact (left) and an offset impact (right).

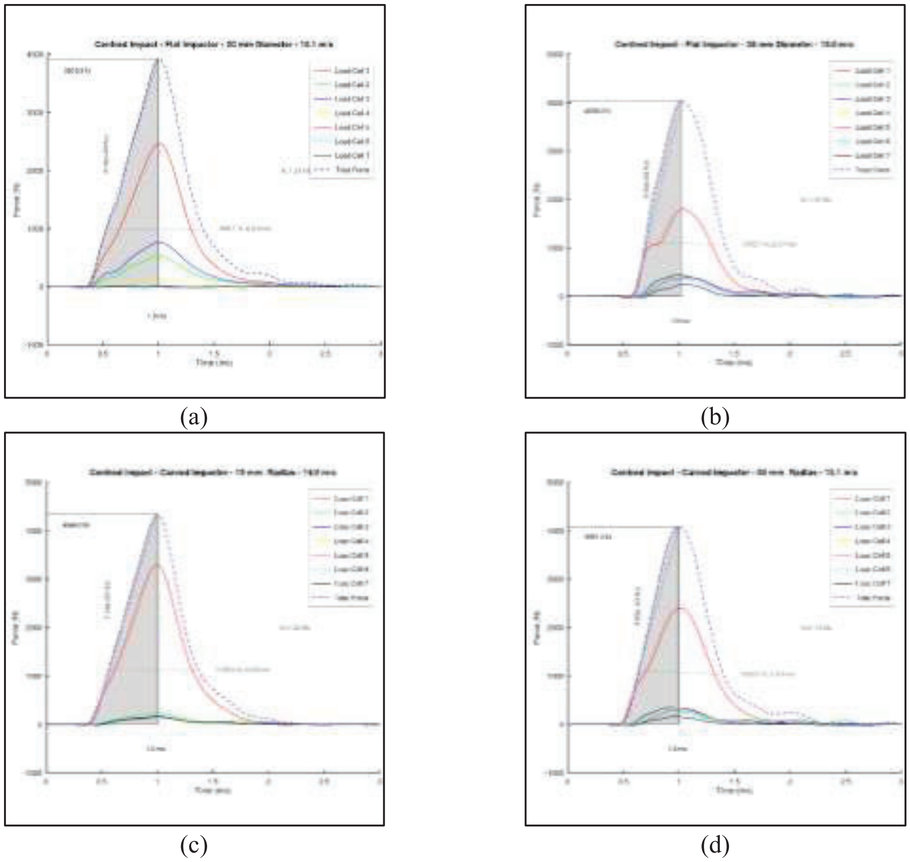

Figure 62. Representative force loading on the BLSH during air cannon testing at 15 m/s.

BHBT testing

The indentation in the clay backing from the 9 mm 124 gr FMJ and the 64-grain FSP helmeted clay impacts are shown in Figure 63 with the corresponding impactor shapes from Table 23 that best matched the indentations. Note that the shell deformations extend beyond the boundary of the projectile's body.

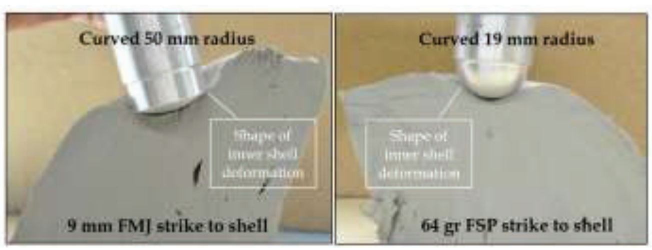

Figure 63. Clay indentations obtained from ballistic helmet strikes compared to rigid impactors used in the BLSH tests.

The curved 50 mm radius of the rigid impactor faces best matched the clay indentation from the backface deformation of the helmet shell for the 9 mm 124 gr FMJ bullet strike, whereas the curved 19 mm radius impactor best matched the indentation from the 64 gr FSP impact. Again, it is noted that the shell deformations extend beyond the outer body of the impactor.

Machine learning model

Before training the SVM model, a preliminary analysis of the BLSH data included a comparison of specific impact parameters for the different impactors. There were promising trends toward identifying the impactor shape based on the BLSH's load cell measurements, however, as there was no single parameter that could decisively identify the impactor shape, more sophisticated methods were required.

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3.1.1 Evaluation and Validation

The procedure described from the implementation of SVM through testing and performance was applied to the BLSH test data to develop a method of identifying the impactor type based on the resultant BLSH force-time histories. Of the 48 shots studied using the SVM model with 12-fold cross-validation, the accuracy was 93.75% with two shots misidentified, Table 25. Therefore, given a set of experimental parameters, the SVM would be able to classify the closest equivalent impactor type during BHBT helmet testing with a high level of accuracy. A one-nearest-neighbour (1-NN) classifier was also trained as a baseline to establish predictive power using a trivial classification method. The 1-NN model, which is often included in published studies as a basis for comparison, had an accuracy of 85.42%. The SVM significantly outperformed the reference classifier with 3/48 misclassified events (compared to 7/48 for the 1-NN model). The high accuracy suggests that ML models can classify impactor shapes by detecting patterns that are not obvious to humans. Further research into alternate ML models is warranted. All testing was performed on the left side of the BLSH. Due to differences in skin pad and hex pad curvatures between the front, rear, and side impact sites, it is not known if the SVM model would be able to distinguish rigid impactor geometries at sites other than the one tested without additional training data.

Table 25. Binary classification confusion matrix.

Impactor Classification	Model Prediction			
	Flat 38 mm	Flat 20 mm	Curved 50 mm	Curved 19 mm
Flat 38 mm	11	-	1	-
Flat 20 mm	-	10	-	2
Curved 50 mm	-	-	12	-
Curved 19 mm	-	-	-	12

3.1.2 Application

The SVM classification model described in Section 6 above and trained using air cannon testing was applied to the BLSH data from the ballistic non-perforating behind helmet deformation impacts. The helmets with full suspension and retention system used for testing were fitted to the BLSH in the as-worn position by a soldier to achieve typical shell offsets. The BLSH load cell data was processed similarly to the BLSH air cannon test data and included the extraction of the 14 input parameters for the SVM. The SVM model classified the new BHBT data (three 9 mm FMJ and three 64-grain FSP) as belonging to the “Flat 38 mm” class. The injury risks are plotted in Figure 64 on Allanson-Bailey’s injury risk curves for fracture, overlaid on the class predicted by the model.

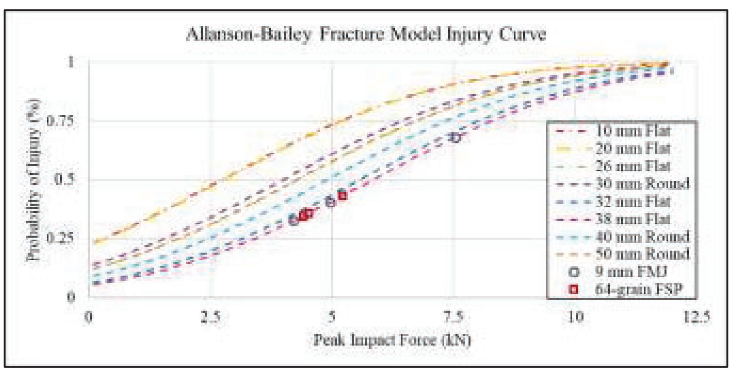

Figure 64. Clay indentations obtained from ballistic helmet strikes compared to impactors used in the BLSH tests.

Here, the boundary conditions between the BLSH/BHT tests and the clay-filled shell tests are inherently different (i.e., presence of liner/retention system and offset, rigidity of BLSH vs clay). It is therefore difficult to directly compare the BHBT profiles predicted by the SVM to the witness testing. Importantly, the projectiles and velocities selected for the analysis were demonstrated to produce different BHBT deformation profiles on the clay witness material.

The clay testing showed that BHBT profiles are different for the two projectiles, but they do not necessarily correspond to what they would be for the BLSH. It would be very useful to develop a method of measuring the actual BHBT impact profile with boundary conditions that match the BLSH to validate the SVM model. Alternate methods such as DIC on the inside surface of a helmet shell would likely provide similar deformation profiles as the clay witness due to similar boundary conditions. The dynamic helmet shell deformation is constrained by the contents (i.e., BLSH headform or operator skull). The SVM suggested that both projectiles produce loading most similar to the Flat 38 mm rigid impactor. This suggests one of the following scenarios:

1. Interactions between the helmet shell and BLSH headform produce similar BHBT profiles for the different projectiles as the maximum deformation is constrained.
2. The presence of a helmet liner/retention system with offset for BLSH testing produce a more distributed load than the clay-filled helmet tests with no liner or offset, thereby biasing the deformation profile. Similarly, the liner and comfort pads present during the BLSH tests may in fact be generating a wider backface profile.
3. The air-cannon data was not representative of the ballistic test conditions. The SVM should have produced different estimates of the impact profile for the two cases but did not because the closest case to both was not particularly representative.

Each of these potential explanations is potentially insightful and could further the understanding of BHBT. First, if the interactions between the helmet system and the headform, which is significantly less compliant, are critical to the proper assessment of BHBT, then an operator's skull also likely provides significantly more resistance than a clay witness. Second, if the presence of shell offset and helmet liner, which are designed to distribute load and provide additional protection, significantly changes the backface deformation profile, the approaches that aim to quantify the deformation of the inner shell surface (i.e., DIC) may have limited applicability to in-theatre events. Third, the fundamental underlying assumption relied upon in this analysis is that the air cannon impacts are representative of the helmet BHBT response during ballistic impacts. Characteristics of helmet BHBT responses have been published [6], (Voo, Improved Repeatability and Reproducibility of the Ballistic Load Sensing Headform, 2016), [14], [18] with varying characteristics which are likely due to the unique response of combat helmets to the specific threat and shot location, the varying stand-off distances between shell and head, and the helmet shell support conditions (e.g., edge clamped, air backed or supported by a liner). As a result, BHBT assessment studies will need to explore the range of responses that can lead to injury.

The *k*-fold cross-validation of the air-cannon model indicates that it is a strong model with high predictability for data similar to training data. SVM classifiers are known to be extremely sensitive to outliers (i.e., test data that is fundamentally different from training data) and unable to extrapolate beyond the training dataset as optimal hyperplanes may have high curvature outside the training bounds. Therefore, a fundamental question in the present study is whether the air-cannon training data conditions (constant cross-sectional loading) is representative of ballistic BHBT loading (decelerating end ballistics). The BHBT tests tend to have a much faster loading and a wider peak but similar maximum load. If further testing is performed using the same approach described herein, it would be beneficial to vary the rigid impactor masses and velocities to more closely match the peaks, slopes, and impulses seen in BLSH/BHBT testing. In theory, if the rigid impactors are designed to match the BHBT deformation and the mass is selected to represent the effective mass of the helmet shell and projectile, and the velocities are selected to represent the shell deformation speed, it may be possible to accurately represent ballistic events using air-cannon testing. The differences in loading curves, combined with the poor ability of SVM to extrapolate to new data not contained within the training data are critical limitations of this approach. By extension, if the air cannon data test conditions, based on elements of the Allanson-Bailey injury risk curves, are not representative of BHBT loading conditions, perhaps their relevance to BHBT injury severity ought to be questioned.

4. CONCLUSION AND RECOMMENDATIONS

Behind helmet blunt trauma is a potential threat when a helmet is struck by non-perforating ballistic projectiles where the resulting local shell deformation can impart significant loading to the head causing skull fracture. According to research conducted by Allanson-Bailey, in addition to the load magnitudes, the risk of skull fracture may also be dependent on the shape of the shell's backface deformation. The Ballistic Load Sensing Headform (BLSH) was used in a series of air cannon and ballistic tests to assess the headform loads and to estimate the profile of the shell's deformation based on characteristics of the headform load measurements. The direct load measurements with the BLSH's seven load cell array did

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not have sufficient spatial resolution to distinguish the load profile of the impacting surface. That said, the characteristics of the resulting force-time data traces showed trends that may offer insight into the impacting surface's profile. A method was developed to combine multiple characteristics of the BLSH's response curves using a Support Vector Machine (SVM) to classify the response for different impactor shapes that were shot directly at the headform. The SVM was shown to be 94% effective at distinguishing between four different impactor shapes used by Allanson-Bailey.

In this study, significant assumptions regarding the applicability of air cannon testing to ballistic events were required. This may have resulted in BHBT events effectively being outliers that are not representative of the physical processes at play. Using a different ML approach that is more robust with respect to outlier sensitivity could help but the training data must still be representative of the test data. In theory, it may be possible to select a rigid impactor profile that is representative of the geometries seen in BHBT testing, tuning their mass to match the effective mass of the helmet shell and bullet, and matching inner shell deformation velocities. If these conditions are met, the applicability of air cannon testing to simulate ballistic BHBT events on the BLSH could be greatly improved. As helmet shell performance, stand-off and backings as well as threats change over time, the characteristics of BHBT simulating impactors may need to be revisited to better reflect current helmet technologies.

Additional limitations are noted with respect to the work of Allanson-Bailey with the use of a Bovine Scapula Model (BSM) as an analogue for fractures to the cranium [6]. While similarities were demonstrated with Raymond [14] when using a multi-parameter logistical regression model, limiting factors remain and are noted to include the scapula surface curvature, skin and bone thicknesses, effective mass, and mode of fracture with respect to the population being studied. Further limitations include the shape, projected area, mass, rigidity, and speed of the impactors used to represent the true dynamic shell deformations and interactions with the cranium for a range of helmet constructions. However, it should be recognized that while rigid impactors provide a first approximation of behind shell interactions, they are a valuable addition to help identify the contributing factors to injury by controlling the impact conditions compared to full helmet system tests with inherent greater variability. Ideally, rigid impactor conditions should span the range of expected responses of the helmet system in-situ for relevant estimation of the injury risk, as with the SVM classification approach being presented.

The discrepancy between the deformation profile seen in the clay witness testing and those predicted by the SVM may be a systemic artefact inherent to the comparison of different processes. The presence of the liner system that distributes force and interactions between the shell and a non-compliant headform may result in a different BHBT profile than when a shell is filled with clay. The objective of this study was to develop a method of predicting the impactor shape on the BLSH. This was achieved for air cannon testing, but it would be useful to have a method of validating the BHBT deformation profile on the BLSH to fully validate the approach.

An alternate development pipeline approach could be proposed, where BHBT tests are performed on clay or using DIC to quantify the deformation profiles. The machine learning model would then be trained and validated on ballistic tests thereby resolving any concerns regarding the applicability of air-cannon data to BHBT events. This method would be significantly more resource-intensive – from the cost of each helmet used in testing to build a dataset sufficiently large for machine learning to be used, to the time taken by technicians after every test to repair and recondition deformed clay. This approach would require a researcher to classify the deformation profile in clay or using DIC for each impact into one of a set of impact profile definitions. The tests would then be repeated on the BLSH to determine the load profiles for each test. Finally, every new BHBT test condition would be performed on the BLSH to assess the force distribution from the load cells, expected deformation profile from the ML classifier, and the injury risk from the combined peak force and deformation profile class using the Allanson-Bailey curves. It is fair to question the relevance of the Allanson-Bailey injury risk curves for BHBT testing due to differences in boundary and impact conditions, and test medium, however, until a more suitable dataset becomes available to the research community, this is arguably the most pertinent reference.

The approach described herein attempts to link BHBT data collected on the BLSH to published injury risk curves using a machine learning classifier based on rigid impactor tests performed using an air-cannon. Each step of the process required assuming the validity of certain aspects (air cannon testing to represent ballistic BHBT events, applicability of Allanson-Bailey injury risk curves to BHBT events, etc.) Addressing limitations identified in this study could improve the presented methodology and ability to link BHBT tests performed on the BLSH to injury risk using machine learning.

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 https://doi.org/10.52202/080042-0011