Original article

ConcussionWatch: A real-time method for concussion detection in athletes

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Abstract
Each year, athletes across the world are injured or killed from 3.8 million sports-related concussions, primarily related to contact helmet sports like football and lacrosse. Despite product development efforts at measuring hit-detection, determining cause of concussion, and predicting recovery, there is a lack of focus on real-time concussion detection for athletes. This study involved the construction of an electronic sensor containing device capable of being placed inside a lacrosse helmet. Proof-of-principle testing demonstrated that the device did not degrade comfort of wear, and was robust enough to withstand limited impacts as would occur during concussion causing hits during games. The electronic sensor stored a feedforward artificial intelligence, neural network model to detect real-time concussions. Uploading and running the neural network on/from the device ensured that the concussion-detecting and measuring functionality of the device was operational without reliance on Bluetooth® or on WiFi. The ML model was based on an online dataset containing actual concussion data correlated with the Head Injury Criterion (HIC) and the Gadd Severity Index (GSI); which in turn, was linearly interpolated with an equal amount of synthetic data. The model returned scores > 0.99 (for a binary decision of concussion/no-concussion) across metrics consisting of accuracy, recall, precision and F1, when tested on hold-out data. Additionally, a mobile app was coded to work in conjunction with the concussion-detection and measurement sensor by recording data that could be viewed by players, coaches, and medical professionals. Constructing the circuit with commercially available and marked-up parts led to a significantly cheaper device than currently available commercial devices; and one that was additionally equipped with real-time concussion detection functionality. The results of the study pose a potential advancement in the development of real-time concussion-detection technology and the ability to protect athletes against brain injury.

Keywords
ConcussionWatch, Concussion, Real-time concussion detection, Machine Learning, Neural network, Brain injury, Inexpensive concussion detection device, Contact sports, Feedforward Network, Athlete

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1. Introduction

Each year, many young athletes are injured or killed from sports-related concussions. There are 3.8 million concussions per year from sports, and 5-10% of athletes suffer from concussions during any particular sports season (1). The sports which result in the most concussions are high-contact ones, particularly those that require the use of helmets, such as football and lacrosse. Lacrosse receives far less attention than football due to the latter's widespread popularity and notorious risk for head injuries, yet it was found that lacrosse had a higher incidence of concussions per 100,000 athletes; at 16% (2).

Interestingly, concussions may not manifest through one single large head impact. While a common assumption is that one blow to the head results in a concussion, such injuries may occur by repeated small impacts, the effects of which may be cumulative over time. All concussions result from sudden impacts on the head causing movement of the brain and allowing it to hit the inside of the rigid skull. Such movements bruise the brain (3). However, repeated movements bruise the brain by sometimes unnoticeable amounts, and thus a concussion may not be diagnosable after one particular hit. The buildup of hits leading to bruising without a concussion diagnosis makes these 'one-more-hit', 'at-the-cusp' concussions more difficult to detect by sensors and medical professionals because the injury is not noticeable until the next incremental 'hit'.

There exist a variety of head impact sensors available on the market. Such sensors are able to measure exposure to head impact, but they lack the necessary sophistication to detect sensitivity to a concussion (4) and subsequently predict the probability that a concussion may have occurred. Importantly, such sensors do not factor the accumulation of hits that may lead to a concussion and rather operate on the assumption that one large blow results in a head injury. Additionally, head impact sensors are not widespread across sports, perhaps due to difficulty in use and high expense. There have also been studies utilizing machine learning to predict concussions. One such study was able to use a ML model to predict recovery time from concussions (5). Another study used machine learning to predict concussion reporting that may be delayed or attended to, too late (6). However, utilizing real-time and machine-based concussion detection is an under-researched area since most current sensors only detect head impacts without analyzing them (7).

Currently, head impacts and the potential for concussion are analyzed using several parameters. The first is acceleration. A force exerted on the skull of an athlete causes an acceleration of the skull but often not the brain, causing the brain to bruise against the skull. Thus, it follows that a more extreme acceleration potentially leads to higher bruising. The Head Injury Criterion (HIC) and the Gadd Severity Index (GSI) are more recent metrics which correlate a head impact to the likelihood of a concussion. Such measurements provide insight and weighting to potential head injuries that occur in athletes (8).

A sensor-based-product to determine impact as well as predict the probability of it being a concussive event – using a Machine Language algorithm; that, in turn, would provide pivotal data to a detection AI model – could hence fulfill an unmet need in this area. Such a product could be useful in calculating the risk of concussion for every impact it detects during the sports season, and therefore in reducing the chances of an athlete continuing to play subsequent to output of an elevated risk or of an outright concussion.

2. Data

2.1 Dataset

A major contribution of this study was the use of a dataset that measured actual impact sustained by college and high school football players on the days of diagnosed concussion. There are multiple datasets on concussion available on Kaggle but most of these either present NFL athlete data or synthetic data. Data on actual concussion statistics pertaining to high school or college athletes is hence scarce. Consequently, the online dataset was used from the study "Head Impact Exposure Sustained by Football Players on Days of Diagnosed Concussion" (8). This study involved a 6-year window of head-impact measurements for college and high school athletes on particular days and information on which days resulted in a concussion. Such diagnosis by a professional would not be available to most high school athletes. The dataset involved 40 ms of head acceleration measurements, recorded when an accelerometer sensor registered over 14.4 g (the threshold was rationalized to be a low level, and hits less than this either did not register or were not believed to correlate to concussion). Data was reported in median and interquartile ranges of athletes' 50^{th} and 95^{th} percentile head impacts on concussion and non-concussion days. Specifically, the head impacts were characterized by peak linear and rotational acceleration, change in velocity, HIC, and GSI. The median number of hits with top 50^{th} and 95^{th} percentile of linear and rotational acceleration sustained by athletes above certain thresholds was also reported for concussion and non-concussion days.

Even so, the above-mentioned dataset reported statistics, but not extensive data. Furthermore, head-impact and concussion correlation were not reported. Therefore, 1000 data points for each non-concussion and concussion days were interpolated from this existing dataset (generating 2000 data points total, on a google sheet (see supplementary file). These points were a facsimile of the actual concussion study and its spread of distribution, because floats for each criterion were randomly selected between quartile and percentile ranges indicated by the study (with their frequency being consistent with that of the original study distribution). It is important to note that min and max values were estimated using quartile ranges, and the number of hits rounded to an integer. This could be therefore construed as synthetic data obtained from linear interpolation of real data.

2.2 Multicollinearity

While statistics such as GSI, HIC, and acceleration were likely to be correlated, no multicollinearity analysis was performed on these variables. It was not the objective of the study to understand the individual contribution of each correlated predictor to the model's outcome; or to infer causality; rather, to predict the probability of a concussion. Furthermore, all these predictor features were relevant to the probability of sustaining a concussion and thus were all used in the machine learning portion of the study.

3. Methods

The objective of the methodology was to decrease the number of dangerous concussions that occur in sports by creating an easy to use and inexpensive sensor. An app to collect and store data was designed to work in conjunction with a machine learning model to accurately detect small concussions that might previously go unnoticed by officials. It is important to note that the sensor was designed specifically for a lacrosse helmet due to the materials available in the study. However, lacrosse, football, and other sports helmets have similar padding structures inside, which leads to similar shock absorption mechanisms and the same potential fit of a device inside the helmet.

3.1 LSTM Neural Network

The first step towards development was to create a neural network that could analyze head impact data and diagnose concussion. For all machine learning training, the dataset was split between training and testing at 80%-20%, and data was normalized in pre-processing on a scale of 0-1.

Initially, a long short-term memory (LSTM) neural network, which recognized patterns and feeds data recursively to learn, was developed on Python to find patterns in the data and diagnose concussions. This LSTM used a dropout of 0.1, an AdamW Optimizer, and was constructed of 4 layers with an average of 256 neurons per layer.

3.2 Feedforward Neural Network

It was decided that for optimal performance and success, the neural network would best be placed on the sensor itself to avoid reliance on Bluetooth® and WiFi during a game. Therefore, using the same dataset, a simple feed-forward neural network was created on Edge Impulse™ (Qualcomm, San Diego, CA, https://edgeimpulse.com). The Neural network architecture is shown in Figure 1. This feedforward network was composed of three layers and 600 total neurons, with a dropout of 0.1. After the model was trained, a library for Arduino (Boston, MA, https://arduino.cc) was created with Edge Impulse™ to store the model, and this was added to the Arduino code for the electronic sensor.

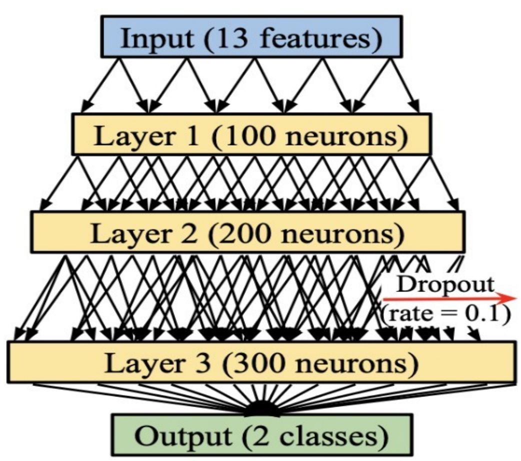

Figure 1. Edge Impulse™ Network. The structure of the simple feed-forward neural network.

3.3 Data Collection Sensor

A sensor was constructed to work in conjunction with the machine learning network to detect head-impacts, store and organize them, load the machine-learning network to detect a concussion in real-time, and transmit user data to the cloud via an app after the game.

An Arduino Nano 33 IoT was used to perform the machine-learning, data storage, and data transferring functions while interfaced with a model H3LIS331DL accelerometer (STMicroelectronics, Coppell, TX) to obtain head impact data. The circuit was powered with a 9V battery and contained an on/off switch and piezo buzzer for alerting the user in the case that a concussion was sustained. The circuit diagram and the assembled circuit is shown in Figures 2 and 3.

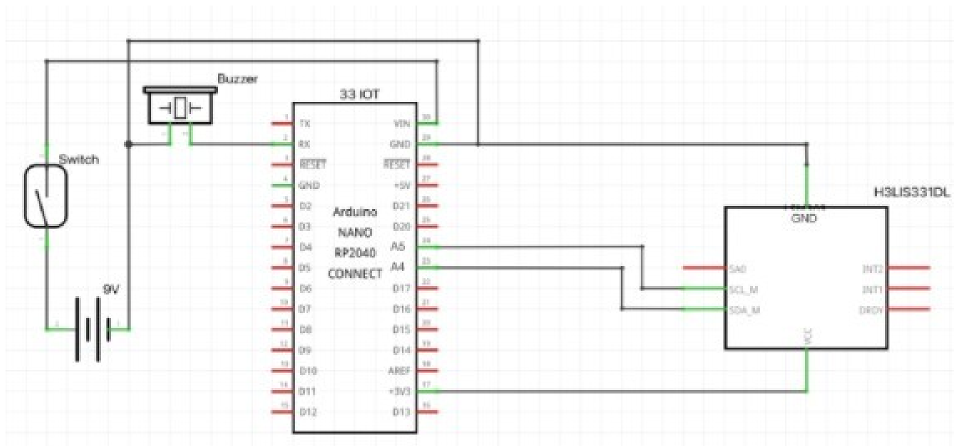

Figure 2. Circuit Diagram. Powered with a 9-volt battery through a switch to the Arduino Nano 33 IOT. Accelerometer and buzzer were powered with pins and 3.3V.

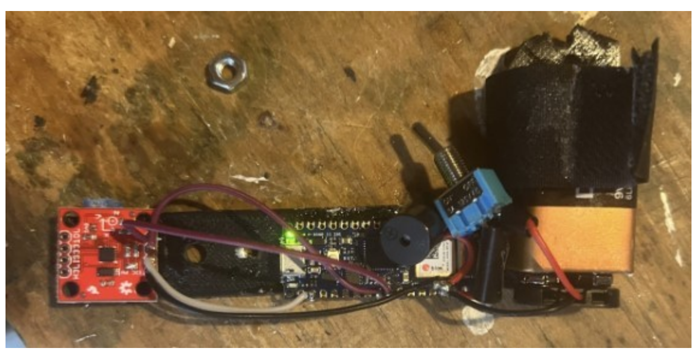

Figure 3. Assembled Circuit. Image of the soldered circuit.

Additionally, a case for the circuit was 3D printed using a generic 3D printer. It had a flat bottom component which the components of the circuit were fastened to with tape and glue in addition to a hollow top component to be placed over the circuit and fastened with two machine screws. Images of the CAD design and the fastened top are shown in Figures 4 and 5.

Figures 6 and 7 show the waterproofed device and the location of the device in the helmet respectively.

The sensor was coded in Arduino and performed several important functions. On being turned on, the 33 IoT continuously read accelerometer data at 1600 Hz. If an acceleration over 14 g was registered, data collection occurred for 40 ms, then the hit (with calculated variables for characterization) was stored in an array. After each hit, the array of hits for that day was analyzed with the machine learning network - if a concussion was detected, the buzzer would be sounded. The 33 IoT also continuously searched for Bluetooth® connection, and upon connection to a phone, updated a notification that involved the sending of the data array to the app on the cloud (explained in section 3.4).

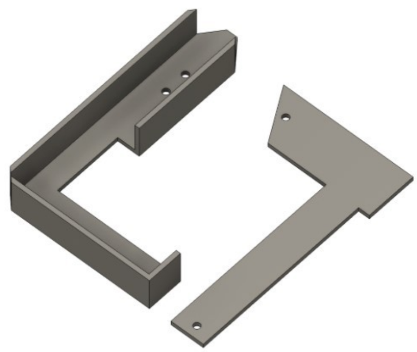

Figure 4. Case CAD Model. The bottom plate (where the electronics are attached) and protective cover, which were fastened with machine screws

Figure 5. Assembled Case Assembled circuit and case.

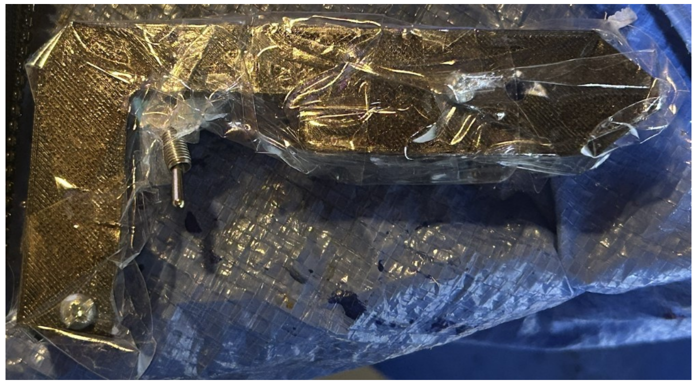

Figure 6. Waterproof Case. The case was deemed to have a waterproof seal when wrapped with packing tape, ensuring that it would not be damaged during use.

Figure 7. Location of Sensor in Helmet. The red dashed lines indicate the location of the sensor in the helmet.

3.4 Mobile Application

An aesthetic and extensive iOS app was coded to work in conjunction with the sensor. The app consisted of five pages: Collect, Set Up, Learn, Data, and Sign Out.

Figure 8 shows the Collect page. As shown, there was the option to connect to the sensor and receive data and likelihood of injury. Collect was the default page and performed the primary function of the app; *viz*, to obtain data from the electronic sensor and store it in the cloud. Collect contained a welcome message and option to connect to the electronic sensor via Bluetooth®. This would be performed after the data was collected after a game. Using Core Bluetooth® Central Manager (CBCentralManager) and Peripheral (CBPeripheral), the Bluetooth® on the phone scanned for an ID and name matching as advertised by the Arduino. Upon finding a matching device, the peripheral delegate listened for an updated characteristic of a certain ID (updated by the Arduino during data sending). Then, the app received the updated characteristic as an array, processed it, and using the user ID (obtained by Firebase™ Authentication) stored the array in the user account in the Firebase™ Realtime Database (Google LLC, Mountain View, CA, https://firebase.google.com).

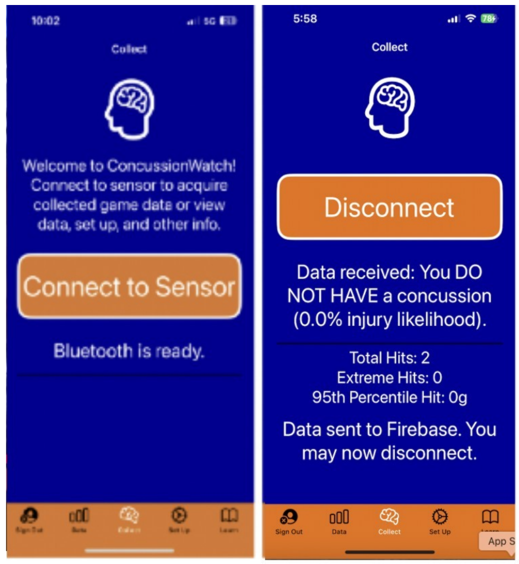

Figure 8. Collect Page

Figure 9. Setup and Learn Pages. These instruct the user on concussions and on using the sensor.

The next pages of the mobile application were Set Up and Learn (Figure 9). Set Up was designed to aid users in setting up their ConcussionWatch sensors. It sectioned receiving and usage into four simple steps: adding the battery, attaching the cover, fastening to the helmet, and using the sensor. An accordion was created for this page so that when each step was tapped, more information with an image was revealed. The Learn page was created to instruct users on concussions themselves. It consisted of three main questions related to concussions with explanations and clipart, and also comprised a chatbot which was coded with a Flask live server (open-source web framework for Python, maintained by the Pallets Projects Organization, https://palletsprojects.com) that queried the Open AI API.

The Data page (Figure 10) showed users' past data displayed in graph form. A heading at the top informed users of the number of concussions and the date of the last one, and then three graphs were displayed with total hits and large linear or rotational hits on each day of use. Concussion days were displayed in red for easy identification. This data was obtained by finding the user ID through Firebase™ Authentication and accessing the Firebase™ Realtime Database for the specific user logged in. The database was populated with sample data or retrieved sensor data during testing, and this was cross-referenced to ensure consistency with data displayed.

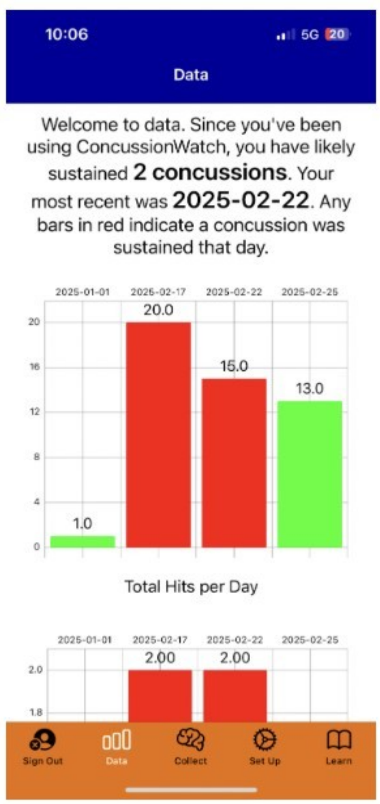

Figure 10. Data Page. The data page features several bar charts and an information header.

Finally, the Sign Out page (Figure 11) signed the user out back to the Sign In page, which prompted email and password or the opportunity to create a new account. This was set up with Firebase™ Authentication to determine if a user existed, or create a new one, and then prove a user ID which would in the future provide for all data sending and access with the Firebase™ Realtime Database.

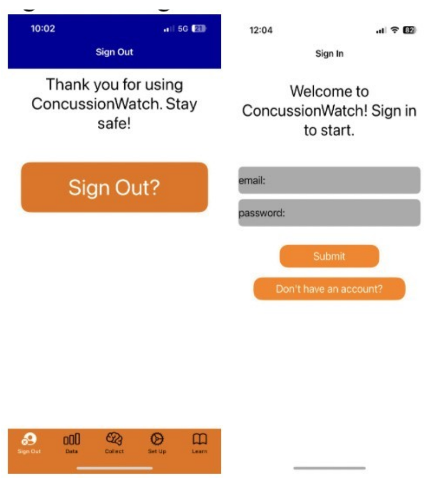

Figure 11. Sign In and Out Pages. Functionality for creating or signing into an account or signing out for anytime and place data access.

4. Results and Discussion

4.1 LSTM Testing

The initial LSTM model achieved an accuracy of 99.75%. Precision was 1.000, and recall was 0.9951. The F1 score was 0.9975. A confusion matrix created after testing demonstrating prediction vs true labels is shown in Figure 12.

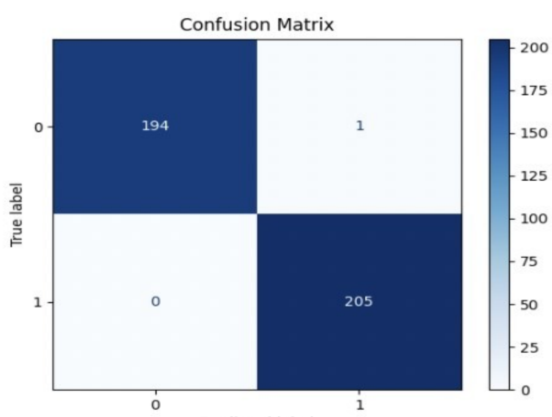

Figure 12. LSTM Confusion Matrix

4.2 Feedforward Testing

The feedforward neural network, created subsequent to the LSTM, due to Arduino constraints, was also tested. This network was extremely, small, only 97.4 KB, yet obtained an accuracy of 95.3% (Figure 13). Importantly, the model was also tested briefly with positive and negative controls (data not shown).

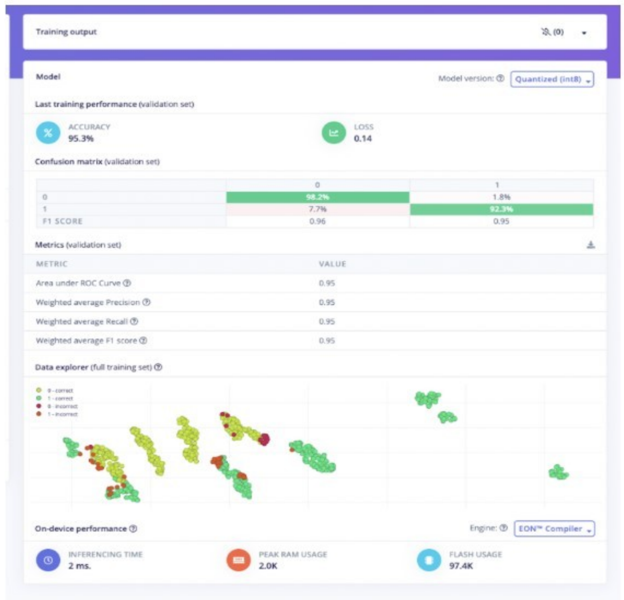

Figure 13. Edge Impulse™ Network. Various metrics on testing, accuracy, network size, and predicted performance.

4.3 Sensor

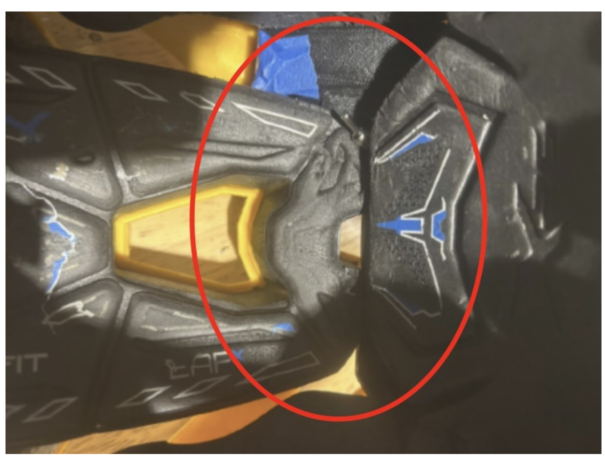

Figure 14. Sensor Placed in Helmet. Once put in the helmet, the sensor could barely be seen and did not affect wearing or use. The outline of the sensor is indicated by a red circle on the image for easier use. Because the sensor was so small, it could not be seen from any angle aside from the one shown.

Placement of the sensor in a helmet was tested to ensure ease of use. The sensor was placed inside the back of the helmet, held by friction and optional masking tape. As seen in Figure 14, the sensor was barely visible when placed for use, yet the on-switch was accessible and could be flipped easily before and after each game. Additionally, the placement of the sensor, as shown, did not affect the wearing of a helmet and could not be felt when the helmet was worn. It is important to note that this is anecdotal data as performance was only tested by the author.

A significant portion of testing different from fit and ergonomic testing was performed. Both raw and calculated values from the accelerometer were printed to the Arduino serial monitor. Additionally, the helmet was repeatedly dropped from a height of ~ 6 feet (~ height of the average athlete), to check for damage. Other impact testing and evaluation was done with procedure that was representative of NFL impacts (9) at 6 locations (front, back, top, side, and bottom) and three slam/drop velocities (10 m/s, 6 m/s, and 3 m/s). The basis of product testing on existing studies and protocols was meant to represent the range of impacts in the NFL so as to represent its viability to be used in-game. After ~ 20 drops or 15 extreme slams, some wires loosened or became detached. However, once this problem was fixed with the addition of more solder, the device became more reliable and robust and did not fail/break after the 15 extreme slam test. The next step of testing would be real and in-game, or recording data during slams. Variable input linear accelerations corresponded to similar rotational, HIC, GSI, and velocity change measurements for test cases selected in the dataset study as well. An example is shown in Figure 15.

	Calculated	Dataset Value	Error
Linear Accel	63.5	63.5	0%
Rotational Accel	2540	2761	8%
HIC	62.12	62.7	0.93%
GSI	93.18	94.4	1.29%
Delta v	2.35	2.31	1.73%

Figure 15. Calculated Metrics Comparison. The comparison of values calculated by the sensor versus a case test of values corresponding to the same linear acceleration described in the original dataset study.

Additionally, the function of the neural network on the Arduino was tested. The network was implemented into the code. Non-concussion scenarios were run by lowering impact thresholds and shaking the accelerometer to trigger analysis. Normally as well, a hit dataset with low enough linear accelerations would be automatically dismissed due to the fact that no concussion would occur. Since testing a concussion scenario would be dangerous, sample concussion data was fed to the network, which triggered the buzzer and returned concussion. This was checked with the serial monitor.

4.4 Application

The entire process from collecting data on the Arduino to transmitting and reading on the app was tested. The Arduino was able to successfully connect to the app and transfer data, which was printed to the screen of the app and saved to Firebase™. Additionally, the Flask code which queried the Open AI API was tested to be functional on the mobile application. Also functional was the display of graphs and information on the data page. While repeated testing of the chatbot did not occur due to the financial constraint of using the Open AI for widespread use, for actual field use, this could be financed or a free option used.

4.5 Perspectives
The sensor, machine learning model, and app functioned as intended. Data was collected and analyzed in real time with a process that was 95.3% accurate. This data along with the result of the analysis was successfully viewed on a smartphone in various forms.

Nevertheless, changes could certainly be made to improve the ConcussionWatch sensor and app. More testing could be conducted in the future, specifically on athletes playing games. The simple 3D-printed prototype could be refined into a final product, as could the app, for better visual appeal. One potential advancement for the mobile application would be to create a version for coaches so that multiple players could be tracked and monitored at the same time. The machine learning model could be trained with more data to be more robust and adaptive. Finally, alternatives to the sensor that could be used in non-helmet sports and potentially worn as a headband could be developed.

5. Limitations
The 2000 data points were linearly interpolated from the referenced dataset (8). It was implicitly assumed that linear interpolation would yield synthetic data which would be a true expanded representation of real data. A dichotomy exists between interpreting this linear interpolation through the application of an ML model which may (or may not) have modeled this data as being non-linear. Consequently, superimposition of these conflating assumptions could have returned accuracy results that may be overly optimistic.

The sensor and helmet testing were performed by/on one individual (the author) and used heuristic procedures not necessarily confirmatory to formal sport impact or concussion guidelines. Hence, all results relating to the sensor should be treated as being anecdotal. The interpolation of data was a reliable method for creating new data points because a lack of data existed in the real world. However, this did contribute to a degree of uncertainty in the results and potentially the overfitting of the machine learning model. To address overfitting, considerable data which the model was not trained on was allotted to testing, and dropout was also used when training the model. Cross-validation and error propagation studies, were not performed.

Secondly, the sensor was designed specifically for a lacrosse helmet. While the padding structures of most helmets are similar, implying similar shock absorption and fit, the narrow focus of testing due to the singular type of helmet was a limitation in the study. The sensor is designed to be specific to the player due to each one's unique Bluetooth® ID, hence helmets would not be interchangeable between players unless data could be transferred and moved between sensors recognizable by ID.

Another limitation was the robustness of hardware. Wires were damaged at points during testing, and while the problem was addressed the potential frailty of the device could not be discounted. Furthermore, the recording frequency of data collection could be increased, which would contribute to a more robust data collection process to ensure that all impacts were measured.

6. Comparison and Business Model

A business model for production and distribution of the ConcussionWatch sensor was constructed to find potential for selling the sensor. Calculations were also made to formulate the business model and predict profits. Figure 16 presents ~ costing to manufacture one ConcussionWatch sensor.

Rudimentary mass manufacturing and distribution costs were calculated. Assuming that soldering and assembling a sensor takes 12 minutes, if a worker is paid an hourly wage of $25 per hour, each sensor costs $5 to solder and assemble. Air freight charges $6/kg, and since the sensor is about a pound, distribution is $3 per sensor. Hence, each sensor is ~ $56, delivered. Marked up 75%, the ConcussionWatch can be sold for $98.

Arduino	$25.50
Accelerometer	$13.50
Battery Adapter	$0.50
Velcro	$0.13
3D Print	$1.00
Screws	$0.06
Shipping	$7.00
Packaging	$0.50
TOTAL	$48.19

Figure 16. Cost Table. The estimated cost for the parts to assemble the ConcussionWatch sensor.

Additionally, the ConcussionWatch sensor can be compared to several leading competitors. First is the Jolt sensor (7). This device is extremely small and can be placed inside a helmet or on a headband. However, this sensor only has three levels of impact measurement and does not report data numerically nor does it report a detected concussion. It costs $99. The Jolt sensor's limited detection capability renders it largely useless because it completely ignores one of the foremost factors in concussions: accumulation of hits over a game. In contrast, ConcussionWatch analyzes total hits in addition to the 50^{th} and 95^{th} percentile hits, thus factoring in the cumulative component.

The next sensor is the Riddell Sideline Response System (10), which costs $350. This sensor boasts accurate measurements but is somewhat large and does not analyze the data. The ConcussionWatch sensor performs the same detection but fits inside a helmet, is significantly less expensive, and undergoes processing, analysis, detection, and storage.

A final option is the Shockbox sensor (11). This sensor is $180 and detects data without angular acceleration, potentially sending alerts and indicating hit intensity with color. Not only is the ConcussionWatch sensor again less expensive, but it measures angular acceleration and has increased accuracy, data metrics, analysis and real-time detection.

A product like ConcussionWatch is likely to be successful in the market, as well as to expand the customer base to include under-served and funding-poor communities due to its differentiating and compelling advantages of real-time detection, cumulative hit detection and accumulation display, and affordability. In addition, its portability; ability to be transferred between athletes without the need to buy dedicated helmets implies that units can be quickly interchanged between or among the most vulnerable (to hits) player positions in games, so long as ID and data transfer can be performed in parallel.

7. Conclusion

An electronic sensor containing device capable of being placed inside a lacrosse helmet was constructed. The electronic sensor stored a feedforward artificial intelligence, neural network model to detect real-time concussions. Uploading and running the neural network on/from the device ensured that the concussion-detecting and measuring functionality of the device was operational without reliance on Bluetooth® or on WiFi. The ML model was based on an online dataset containing actual concussion data correlated with the Head Injury Criterion (HIC) and the Gadd Severity Index (GSI); which in turn, was linearly interpolated with an equal amount of synthetic data.

Sample calculated values for rotational acceleration, HIC, GSI, and change in velocity were consistent with those in the dataset research study, as were several test cases input into the neural network while on Arduino. The ML model returned scores > 0.99 (for a binary decision of concussion/no-concussion) across metrics consisting of accuracy, recall, precision and F1, when tested on hold-out data.

Proof-of-principle product development and testing involved measuring shake accelerations. Measurements in test cases were consistent with accelerations and forces expected by gravity and shaking, indicating reasonable accuracy. Furthermore, the device did not degrade comfort of wear, and was robust enough to withstand limited impacts as would occur during concussion causing hits during games.

Additionally, a mobile app was coded to work in conjunction with the concussion-detection and measurement sensor by recording data that could be viewed by players, coaches, and medical professionals. The sensor was able to connect to the app, and data was sent and accessed via the Firebase™ Realtime Database.

Constructing the circuit with commercially available and marked-up parts led to a significantly cheaper device than currently available commercial devices; and one that was additionally equipped with real-time concussion detection functionality. The viability of the sensor data collection, sending, and display process was evidentiary of the potential of ConcussionWatch to be used in-game, and the results of machine learning analysis and testing provided evidence that a real-time, concussion detecting device could detect concussion causing hits as well as display the accumulation of hits at the 50th and 95th percentile during games.

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I would like to thank my in-school mentors Dr. Ellsworth and Mr. Queenan for providing help and guidance on the process of conducting research.

Conflict of interest
The author holds a provisional patent (#63/790,859) for ConcussionWatch.

Supplementary file
Base datasheet from Reference 8, with expanded and interpolated data and analysis

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