

Can an inertial measurement unit, combined with machine learning, accurately measure ground reaction forces in cricket fast bowling?

Joseph W. McGrath, Jonathon Neville, Tom Stewart, Matt Lamb, Peter Alway, Mark King & John Cronin

To cite this article: Joseph W. McGrath, Jonathon Neville, Tom Stewart, Matt Lamb, Peter Alway, Mark King & John Cronin (09 Nov 2023): Can an inertial measurement unit, combined with machine learning, accurately measure ground reaction forces in cricket fast bowling?, Sports Biomechanics, DOI: [10.1080/14763141.2023.2275251](https://doi.org/10.1080/14763141.2023.2275251)

To link to this article: <https://doi.org/10.1080/14763141.2023.2275251>



© 2023 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.



Published online: 09 Nov 2023.



Submit your article to this journal [↗](#)



View related articles [↗](#)



View Crossmark data [↗](#)



Can an inertial measurement unit, combined with machine learning, accurately measure ground reaction forces in cricket fast bowling?

Joseph W. McGrath ^{a,b,c}, Jonathon Neville ^a, Tom Stewart ^{a,d}, Matt Lamb^e, Peter Alway ^{e,f}, Mark King ^e and John Cronin ^a

^aSports Performance Research Institute New Zealand, AUT University, Auckland, New Zealand; ^bManukau Institute of Technology School of Sport, Auckland, New Zealand; ^cParamedicine and Emergency Management, School of Health Care Practice, AUT University, Auckland, New Zealand; ^dHuman Potential Centre, AUT University, Auckland, New Zealand; ^eSchool of Sport, Exercise and Health Sciences, Loughborough University, Loughborough, UK; ^fEngland & Wales Cricket Board

ABSTRACT

This study examined whether an inertial measurement unit (IMU) could measure ground reaction force (GRF) during a cricket fast bowling delivery. Eighteen male fast bowlers had IMUs attached to their upper back and bowling wrist. Each participant bowled 36 deliveries, split into three different intensity zones: low = 70% of maximum perceived bowling effort, medium = 85%, and high = 100%. A force plate was embedded into the bowling crease to measure the ground truth GRF. Three machine learning models were used to estimate GRF from the IMU data. The best results from all models showed a mean absolute percentage error of 22.1% body weights (BW) for vertical and horizontal peak force, 24.1% for vertical impulse, 32.6% and 33.6% for vertical and horizontal loading rates, respectively. The linear support vector machine model had the most consistent results. Although results were similar to other papers that have estimated GRF, the error would likely prevent its use in individual monitoring. However, due to the large differences in raw GRFs between participants, researchers may be able to help identify links among GRF, injury, and performance by categorising values into levels (i.e., low and high).

ARTICLE HISTORY

Received 24 July 2022
Accepted 17 January 2023

KEYWORDS

IMU; wearable sensors; injury prevention; performance enhancement; sports technology

Introduction

Cricket fast bowlers have more injuries than any other playing position (Orchard et al., 2016). It is commonly accepted that genetic susceptibility, technique, and bowling workload determine whether fast bowlers get injured (Perrett et al., 2020). However, the definition of bowling workload has come under debate recently (Constable et al., 2021; McGrath et al., 2021; McNamara et al., 2015b; Perrett et al., 2020). Previous injury prevalence studies have used this term to describe bowling volume—the number of deliveries performed in a session. Although research has linked a high and low weekly,

CONTACT Joseph W. McGrath  joey.mcgrath@aut.ac.nz

© 2023 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.

This is an Open Access article distributed under the terms of the Creative Commons Attribution-NonCommercial-NoDerivatives License (<http://creativecommons.org/licenses/by-nc-nd/4.0/>), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited, and is not altered, transformed, or built upon in any way. The terms on which this article has been published allow the posting of the Accepted Manuscript in a repository by the author(s) or with their consent.

monthly and yearly bowling volume to injury (McNamara et al., 2017), it does not acknowledge that deliveries are bowled at different intensities, which may exert different levels of stress on the body.

Reasons for the omission of intensity data in research stem from the fact that there are no accepted measures of bowling intensity (Perrett et al., 2020). Potential measures include a rating of perceived intensity, ball release speed, and ground reaction forces (GRF), with the latter two requiring considerable outlay due to the specialist equipment required. A possible solution to overcome this barrier could be to use a wearable inertial measurement unit (IMU). An IMU typically consists of an accelerometer and gyroscope, which measure linear acceleration (measured in g-force) and angular velocity (degrees per second), respectively. Researchers have used IMU data in combination with machine learning to accurately predict bowling volume (Jowitt et al., 2020; McGrath et al., 2019; McNamara et al., 2015a) and measures of bowling intensity—ball release speed and perceived intensity (McGrath et al., 2021).

Although bowling speed and perceived intensity provide a more rounded measure of bowling workload, they do not provide information regarding the GRFs endured during the delivery phase. In fast bowlers, front foot GRFs are, on average, 6.7 times body weight (BW) for vertical GRF and 4.5 BW for horizontal GRF (King et al., 2016; Worthington et al., 2013). In cricket, GRF is measured in a specialised lab using a force plate embedded in the bowling crease. Typical measurements include peak force, impulse, and loading rate during front foot contact, as these are related to performance in cricket (King et al., 2016). The need for specialised equipment has meant that insufficient GRF data has been collected to investigate the long-term link with injury. It has been hypothesised that exposure to repeated high magnitude ground impacts combined with high spinal rotation may be a significant cause of acute and chronic injuries (Bartlett et al., 1996; Crewe et al., 2013; Hurrion et al., 2000; Senington, 2019). Therefore, an IMU-based estimate of GRF might provide a practical solution for monitoring GRF in the field, over time.

There has been a recent emergence of studies trying to predict GRF from IMU data in sports and physical activities. Callaghan et al. (2020) compared GRFs derived from a force plate against trunk- and tibia-mounted IMU force signatures in cricket fast bowlers. However, only a mixed reliability ($CV = 4.23\text{--}18.17\%$) between the two measures was found. The lack of a one-to-one relationship between IMU estimates and GRFs could be because the body has shock-absorbing properties and is not a fixed rigid system (Simons & Bradshaw, 2016). Therefore, the impact acceleration is attenuated while travelling up the kinetic chain to the IMU mounting point (Lafortune et al., 1996; Simons & Bradshaw, 2016). Although it is unlikely that IMUs placed on the body will record force information directly comparable to GRFs at the ground-foot interface, McGrath et al. (2022) did find a strong correlation between GRFs, ball release speed, and perceived intensity in fast bowlers. This coupled with the previously mentioned studies that accurately measured these variables with machine learning means it could be possible to reasonably estimate force plate-derived GRF from IMU data.

Recently, machine learning has been used with IMU data to estimate GRF in sidestepping (mean absolute percentage error (MAPE) = 19.7% BW) (Johnson et al., 2019), running (MAPE = 29.7%) (Johnson et al., 2019), and ballet jumps (unilateral landings, root-mean-square error (RMSE) = 0.42 BW; bilateral landings, RMSE = 0.39) (Hendry et al., 2020). To the authors' knowledge, no studies have

used the IMU's gyroscope and the accelerometer to estimate GRF, which may improve results. This is due to providing the models with more orientation and angular velocity information, which may help estimate overall force (Hendry et al., 2020).

Given the potential benefits of monitoring GRF in cricket fast bowlers and recent evidence of using IMU data to estimate GRF in other sports, this study aims to: (1) determine whether an IMU combined with machine learning can estimate GRFs in fast bowlers; and (2) to determine if results improve with the addition of gyroscope data. Based on the existing literature, it was hypothesised that an IMU and machine learning would be able to estimate GRF with similar accuracy to other studies. Furthermore, it was hypothesised that the addition of gyroscope data would improve all GRF estimates.

Materials and methods

Participants

Eighteen male pace bowlers from the Loughborough University cricket academy were recruited. All participants were 18 years or older (mean age 19.4 ± 1.2 years), and 16 bowlers were right-handed bowlers. The mean height was 183 cm (SD = 7.3 cm), and the mean mass was 78.5 kg (SD = 10.5 kg). Participants had no reported injuries at testing, and written informed consent was obtained from each participant. Seventeen bowlers were sub-elite, playing at a premier club level, and one bowler was elite, having played first-class cricket. Ethics was approved by Loughborough University's Ethics Committee (reference 2020–2274–1855).

Design

This study used a cross-sectional design with data collected from a single testing session. All data were collected on an indoor artificial pitch at the National Centre for Sport and Exercise Medicine (NCSEM) biomechanics laboratory at Loughborough University with sufficient space for a full run-up.

Testing session

Participants had their height and body mass measured and performed their regular warm-up. They were then instructed to bowl 36 deliveries at a chosen line and length, split evenly between three perceived intensity zones—Low = 70% of maximum perceived bowling effort, Medium = 85%, and High = 100% – in random order. These intensities were chosen as they cover the most likely range that a bowler would perform during training and a competitive match. The force plates were positioned at the popping crease to record the GRF of the front foot during the delivery phase. A total of 554 deliveries were recorded for analysis, with 94 deliveries omitted from nine participants due to the failure of an IMU to record (14 deliveries) or participants not landing with their front foot on the force plate (80 deliveries).

Equipment

Two Blue Trident IMUs (IMeasureU, Auckland, New Zealand) were attached to the upper back (around T1) and the bowling wrist (where a regular watch would be positioned). These locations were chosen due to the following reasons. First, their practicality in the ease of application, as IMUs can be easily applied to a vest or watch. Secondly, it is unlikely to get in the way when bowling or fielding. Lastly, the previously mentioned studies have shown both locations correlate and can predict other bowling workload measures (bowling volume, ball release speed, perceived intensity).

Each IMU consisted of a low measurement accelerometer (1122 Hz, ± 16 g), a high measurement accelerometer (1600 Hz, ± 250 g), and a gyroscope (1125 Hz, $\pm 2000^\circ/\text{s}$). In reference to the anatomical position, the wrist IMU was orientated so that the x-axis was aligned with the vertical axis of the body, y was aligned with the medial-lateral axis, and z was aligned with the anterior-posterior axis. The upper back IMU was orientated so that the x-axis was aligned with the vertical axis of the body, y was aligned with the medial-lateral axis, and z was aligned with the anterior-posterior axis. GRFs were measured using two Kistler force platforms sampling at 1000 Hz (Type 9287B, Kistler AG, Switzerland). Ball release speed was calculated using an 18-camera retro-reflective motion analysis system (Vicon, MX13, OMG Plc, Oxford, UK) sampling at 300 Hz. Two reflective markers were placed on the ball. The velocity was calculated using the change in displacement from the first two frames after ball release divided by the change in the time between the frames.

Data pre-processing and feature computation

Force plate: To determine the start and end of front foot contact on the force plate, the magnitude was first calculated by taking the square root of the sum of the x, y, and z-axis squares. A dynamic window for each delivery was created to determine the start and end of front foot contact. The window started at the first sample ≥ 35 N retrospectively from the peak magnitude and ended when it returned to ≤ 35 N post peak magnitude. The 35 N threshold was chosen after observing the force plate data. If the force plate threshold was set to a more conventional 20 N, artefact caused by the steps prior to front foot contact would trigger the force plate in some bowlers. The data from each delivery were then visualised to identify and remove errored trials (i.e., partial foot contacts). Raw data from the y-axis (horizontal) and z-axis (vertical) were used to calculate peak force, impulse, and loading rates using a custom algorithm created in MATLAB R2021a. Specifically, for the horizontal and vertical axis, the impulse was calculated by determining the area under the curve using trapezoidal numerical integration, and the loading rate was calculated by dividing the peak force by the time from initial foot contact to the time of the peak force (Hurrion et al., 2000). GRFs were then normalised to each participant's body weight and expressed in bodyweights (Senington et al., 2018).

IMUs: For both IMUs, a fourth-order 1 Hz Butterworth low pass filter was used for baseline removal (Kautz et al., 2017; Mlakar & Luštrek, 2017). Event detection of bowls was performed by calculating the magnitude of the gyroscope's x, y and z-axis and identifying peaks $> 500^\circ/\text{s}$ (McGrath et al., 2021, 2019). An event detection window of 3 seconds was used to isolate each event. The window was broken into pre-delivery

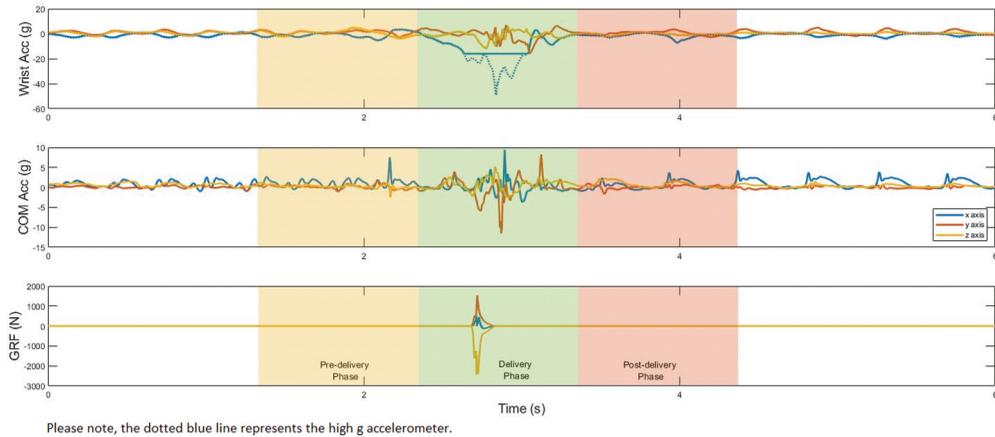


Figure 1. Inertial measurement unit and force plate traces from a single delivery.

(starting and ending 1.5 and 0.5 seconds before the gyroscope peak, respectively), delivery (0.5 seconds before and after the gyroscope peak), and post-delivery (starting and ending 0.5 and 1.5 seconds after the gyroscope peak, respectively). An example of the IMU and force plate traces from a single delivery can be seen in [Figure 1](#)

Features were then extracted within each of the three phases from the time and frequency domains using MATLAB (release 2021b, The MathWorks, Inc., MA, USA). A total of 282 features were computed from the individual axes and the magnitude of the accelerometer and gyroscope channels. The features were similar to Kautz et al. (2017) and included the mean, standard deviation, maximum, minimum, skewness, kurtosis, amplitude, frequency, energy, the position of the maximum, the position of the minimum, as well correlations between x, y and z axes.

Model training and testing

Three machine learning models—random forest (RF), linear support vector machine (LSVM), and gradient boosting (XGB)—were used to predict GRF for each IMU separately. These were chosen because they have been previously effective at classifying bowling volume, ball release speed, and perceived intensity zone with IMUs located on the thoracic back, lumbar back, and wrist (Jowitt et al., 2020; McGrath et al., 2021, 2019).

All machine learning models were trained and tuned in R (R Core Team, Austria) using the caret package. As a pre-processing step, all features with zero variance and those that were highly correlated with other features ($r > 0.90$) were removed. Optimal model hyperparameters were determined using 10-fold cross-validation. The optimal values were chosen based on optimising root mean square error. Leave-one-participant-out cross-validation was used to evaluate the final models.

Statistical analysis

The accuracy of each model was expressed as the mean absolute error (MAE) and mean absolute percentage error (MAPE). The results from each cross-validation iteration were

used within a two-way repeated-measures ANOVA to compare the MAE across the three models and two IMU positions. Model assumptions (i.e., no significant outliers, dependent variable normality, sphericity) were checked before fitting each model using the 'afex' R package. Both models violated the sphericity assumption and were adjusted using the Greenhouse-Geisser sphericity correction. Estimated means and pairwise contrasts (between models and between the two IMUs) were estimated using the 'emmeans' package, with multiple comparisons adjusted using the Holm method. An a priori alpha of 0.05 was used for all analyses.

Results

Table 1 shows the mean, standard deviation, and range for ball release speed and GRF across intensity zones for all participants. There was an increase in mean ball release speed, peak force in the horizontal and vertical axes, and loading rate in the horizontal and vertical axes with a corresponding increase in the perceived intensity zone. There was also a large range between participants for the average minimum and average maximum values across all GRFs.

Table 2 shows the model accuracy for predicting peak force from the upper back IMU and the wrist IMU. The results for accelerometer data and combined accelerometer and

Table 1. The mean, standard deviation, and range for ball release speed and ground reaction forces across intensity zones for all participants.

Variable	Low			Medium			High		
	Mean	SD	Range	Mean	SD	Range	Mean	SD	Range
Ball release speed (km·h ⁻¹)	104.46	5.96	31.79	107.53	5.56	31.79	112.8	6.32	30.04
Peak_y (BW)	2.6	0.71	4.31	2.73	0.73	4.31	3.08	0.87	4.93
Peak_z (BW)	5.05	1.19	6.75	5.24	1.28	6.75	5.76	1.63	7.89
Impulse_y (BW·s)	0.05	0.04	0.22	0.05	0.04	0.22	0.06	0.04	0.23
Impulse_z (BW·s)	0.4	0.08	0.71	0.39	0.08	0.71	0.39	0.08	0.45
Loading rate_y (BW·s ⁻¹)	24.66	9.12	51.09	26.63	9.26	51.09	29.91	10.95	57.36
Loading rate_z (BW·s ⁻¹)	47.45	16.2	99.92	50.95	16.11	99.92	55.83	19.89	97.18
Average contact time (s)	0.37	0.09	0.6	0.36	0.07	0.47	0.35	0.08	0.39

Table 2. Predicted peak force values.

Model	MAPE				RMSE (BW)			
	Upper back		Wrist		Upper back		Wrist	
	Vertical (Z)	Horizontal (Y)						
Accelerometer only								
RF	24.9	27.5*	26.8	25.7	1.36	0.78	1.47	0.77
XGB	25.2	28.9	28.9	25.2	1.49	0.84	1.68	0.79
LSVM	22.1	25.2	22.1	26.7	1.30	0.75	1.27	0.79
Accelerometer and gyroscope								
RF	23.6	24.8	25.5	26.1	1.29	0.71	1.41	0.78
XGB	23.7	25.8	27.0	27.5	1.38	0.76	1.52	0.83
LSVM	22.4	24.1	23.1	27.4	1.31	0.73	1.34	0.82

Key: LSVM = Linear support vector machine; MAPE = Mean absolute percentage error; RF = Random forest; RMSE = Root mean square error; XGB = Gradient boosting. * = Significantly different from the corresponding model and axes in the accelerometer and gyroscope dataset.

Table 3. Predicted impulse values.

Model	MAPE				RMSE (BW·s)			
	Upper back		Wrist		Upper back		Wrist	
	Vertical (Z)	Horizontal (Y)						
Accelerometer only								
RF	18.5	280	16.6*	288	0.07	0.04	0.06	0.04
XGB	19.6	280	18.1	233	0.08	0.04	0.07	0.04
LSVM	17.1^	296	20.2	221	0.07	0.05	0.08	0.04
Accelerometer and gyroscope								
RF	17.1~	255	16.4	249	0.07	0.04	0.06	0.04
XGB	21.6^	220	18.0	286	0.09	0.04	0.08	0.04
LSVM	16.2^~	228	19.3	215	0.06	0.04	0.07	0.04

Key: LSVM = Linear support vector machine; MAPE = Mean absolute percentage error; RF = Random forest; RMSE = Root mean square error; XGB = Gradient boosting. ^ = Significantly different from the corresponding model and axes when using the wrist IMU. ~ = Significantly different from XGB using the same IMU and dataset. * = Significantly different from LSVM using the same IMU and dataset.

gyroscope data are shown. Although there were no significant differences between the models, LSVM generally performed better for predicting vertical (MAPE = 22.1%) and horizontal GRF (MAPE = 24.1%) using the upper back IMU, and vertical GRF (MAPE = 22.1%) using the wrist IMU. The upper back IMU tended to produce slightly less error (although non-significant) than the wrist. Similarly, the combined accelerometer and the gyroscope data tended to have slightly better results than the accelerometer data alone, although these differences were not significant.

Table 3 shows the model accuracy for predicted impulse values. For the vertical axis, the best results were seen with the upper back IMU and the LSVM model when using accelerometer and gyroscope data (vertical axis, MAPE = 16.2%). This model was also significantly better than the XGB model ($p = 0.003$) and the corresponding model for the wrist IMU ($p = 0.006$). Both the RF and XGB models produced better results using the wrist IMU, but the LSVM model tended to provide better results when using data from

Table 4. Predicted loading rate values.

Model	MAPE				RMSE (BW·s ⁻¹)			
	Upper back		Wrist		Upper back		Wrist	
	Vertical (Z)	Horizontal (Y)	Vertical (Z)	Horizontal (Y)	Vertical (Z)	Horizontal (Y)	Vertical (Z)	Horizontal (Y)
Accelerometer only								
RF	35.1^	37.3	39.9*	38.5	17.1	9.51	19.7	9.92
XGB	37.5	40.9	38.7	41.6	19.2	10.95	20.9	11.32
LSVM	36.3	42.0*	33.3	39.2	18.9	10.86	17.3	10.35
Accelerometer and gyroscope								
RF	33.6^	33.6^~	39.2	39.5	16.7	8.88	19.7	10.14
XGB	35.2	38.2^	37.9	43.9	18.8	10.18	19.2	11.42
LSVM	32.6	36.9	36	40.8	16.8	9.7	18.1	10.57

Key: LSVM = Linear support vector machine; MAPE = Mean absolute percentage error; RF = Random forest; RMSE = Root mean square error; XGB = Gradient boosting. * = Significantly different from the corresponding model and axes in the accelerometer and gyroscope dataset. ^ = Significantly different from the corresponding model and axes when using the wrist IMU. ~ = Significantly different from XGB using the same IMU and dataset. * = Significantly different from LSVM using the same IMU and dataset.

the upper back IMU. Regarding the horizontal axis, the variability among participants led to large MAPE scores when estimated from leave-one-subject-out cross-validation.

Table 4 shows the model accuracy for predicting the loading rate. The LSVM model had the best vertical GRF estimate (MAPE = 32.6%), and the RF model had the best horizontal GRF estimate (MAPE = 33.6%). In general, less error was observed when predicting vertical axis GRF and using the combined accelerometer and gyroscope datasets.

Discussion and implications

This study examined whether an IMU located either on the upper back or bowling arm could estimate GRFs with the assistance of machine learning. In all but two cases, the IMU located on the upper back had the best results for measuring peak force (MAPE = 22.1%, 24.1%), impulse (MAPE = 16.2%, RMSE = 0.04 BW·s) and loading rate (MAPE = 32.6%, 33.6%) in both the vertical and horizontal axis, respectively. This is not surprising as attenuation would occur as the force travels up through the lower limbs and into the trunk before progressing to the upper limbs. However, only a few cases showed a significant difference between IMU locations, which means the wrist can also be an effective IMU placement site. This may be partly explained by GRF being correlated with ball release speed (McGrath et al., 2022) and the wrist being the most accurate location to measure ball release speed (McGrath et al., 2021, 2022).

The LSVM was the most consistent model, with the best result in 13 out of the 24 outcomes examined. RF, however, was the most consistent at measuring horizontal loading rate using both the upper back and the wrist IMUs. This differed from two previous studies that found XGB provided the best results when estimating ball release speed and perceived intensity zone (McGrath et al., 2021, 2022). It is difficult to unravel why XGB performed poorly compared to the other models on this dataset. However, this is consistent with what has been termed the ‘no-free lunch theorem’, where machine learning models will not perform equally well on all problems (Gomez & Rojas, 2016).

To the authors’ knowledge, this is the only study to use accelerometer and gyroscope data to predict GRFs. In seven of the 12 comparisons, the addition of gyroscope data improved the overall accuracy of results, although these differences were statistically non-significant. Furthermore, the accelerometer only data had the best overall results for peak force in the vertical axis. This goes against our hypothesis that gyroscope data would improve all GRF measures due to GRF being correlated with ball release speed, and the gyroscope being the most important sensor when predicting ball release speed (McGrath et al., 2022, 2021). Future researchers and developers should consider the modest benefits in accuracy against the increased data volume, processing, and sensor requirements when incorporating a gyroscope.

It is hard to compare the results from the current study to Callaghan et al. (2020). This is because the authors only compared overall force signatures to a force plate and did not predict GRFs from individual deliveries. It is also challenging to compare results against studies that have used IMUs and machine learning to predict GRF in other sports. This is because most studies display results in either MAE or RMSE (Hendry et al., 2020; Wouda et al., 2018), which are generally proportional to the magnitude of GRF observed. Cricket has a relatively high average GRF and possibly greater inter-individual differences

compared to other sports, likely resulting in higher MAE and RMSE scores. However, the results obtained confirmed our hypothesis as they were comparable to similar studies that displayed MAPE to estimate peak GRF in running and sidestepping drills (19.1–29.7% for vertical peak GRF, 21.8% for horizontal peak GRF) (Johnson et al., 2019; Stetter et al., 2019). Interestingly, these studies used deep learning instead of the more conventional machine learning models used in the current study. Therefore, it is debatable whether more advanced machine learning techniques are warranted for estimating GRF using IMUs.

It is unclear why error rates are higher than other bowling workload metrics in cricket (i.e., ball release speed) (McGrath et al., 2022). Cricket is a complex movement where the trunk experiences all three planes of motion during front foot contact. The high angular rotation has been associated with errors in acceleration data due to the crosstalk between sensing axes (Callaghan et al., 2020; Kavanagh & Menz, 2008). Furthermore, the IMUs are unlikely to be at the centre of mass during front foot contact, which was seen as a major limitation for achieving accurate GRF estimates (Gurchiek et al., 2017; Pogson et al., 2020).

Practical implications

Although results were similar to other studies that have measured GRF in running and sidestepping, it is unlikely that a measurement system with a MAPE of 22.1% for vertical and horizontal peak force would be useful for individual monitoring. Specifically, a previous study by McGrath et al. (2022) showed that the difference in peak force between the high and low intensity deliveries was 0.67 and 0.46 BW in the vertical and horizontal directions, respectively. The corresponding RMSE of the 22.1% error observed in this study is 1.29 and 0.71 BW, respectively. This means that such a system could not accurately differentiate GRFs across different zones of perceived bowling intensity. However, as there was a large range between participants for all GRFs, researchers may benefit from categorising values into levels (i.e., low and high). Collecting a large amount of data may help identify links among GRFs, injury and performance.

Limitations and future directions

There are several limitations that the reader needs to be aware of when interpreting these results. Firstly, although the sample size is considered large compared to similar studies, the generalisability of the models could be questionable. A model with a high degree of generalisability means it will work well on a range of cricketing populations. The study sample may not be representative of the wider fast bowling community. There is likely a larger variation in GRFs between academy fast bowlers compared to elite bowlers. Future studies should include a broader range of participants, such as juniors, females, and bowlers of varying abilities. This is important as these playing groups have similar injury rates to elite players (Forrest et al., 2017; Jacobs et al., 2021). Secondly, approximately half the run-up was not captured from all bowlers due to a technical issue with recording. As bowling run-up velocity is linked with GRF (Salter et al., 2007), more data relating to the run-up might improve model accuracy.

Although not a study limitation, researchers may consider using various other techniques to improve model performance. One option could be to train individualised models on each athlete or each type of bowling style (e.g., side-on, front-on, or mixed action). Individualised models may also help mitigate the inter-player variability evident when examining the horizontal impulse data. However, this method would require more individuals to get tested on a force plate which is one of the limitations this study was trying to eliminate. Lastly, researchers could look at other IMU locations (i.e., the front leg or sacrum) or combine information from multiple IMUs. However, Hendry et al. (2020) found that a single IMU on the sacrum was more accurate than IMUs located on five other sites (including the front leg and upper back) or a combination of data from all six IMUs. The locations in the current study were chosen due to usability. For example, an IMU positioned on the lower back may not be suitable in cricket due to players diving. Furthermore, as McGrath et al. (2021) found, the current positions can accurately measure a range of bowling load parameters, so it would potentially be a barrier for use if athletes had to wear two or more IMUs.

Conclusion

This study determined whether an IMU can measure GRF in cricket fast bowling. Results showed a MAPE of 22.1% for vertical and horizontal peak force, 24.1% for vertical impulse, and 32.6% and 33.6% for vertical and horizontal loading rates, respectively. The LSVM model had the most consistent overall results. However, there was variability in model performance, with RF having the best results for measuring horizontal loading rate. Compared to just using accelerometer data alone, the results tended to show a small benefit when combining data from the accelerometer and gyroscope. Although results were similar to other papers that have estimated GRF, the error would likely prevent its use in individual monitoring. However, due to the large differences in raw GRFs between participants, researchers may be able to identify links between injury and performance by categorising values into levels (i.e., low and high).

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

The author(s) reported there is no funding associated with the work featured in this article.

ORCID

Joseph W. McGrath  <http://orcid.org/0000-0001-5597-3596>

Jonathon Neville  <http://orcid.org/0000-0001-8826-6839>

Tom Stewart  <http://orcid.org/0000-0001-5915-3843>

Peter Alway  <http://orcid.org/0000-0003-4062-665X>

Mark King  <http://orcid.org/0000-0002-2587-9117>

John Cronin  <http://orcid.org/0000-0002-8889-0911>

References

- Bartlett, R. M., Stockill, N. P., Elliott, B. C., & Burnett, A. F. (1996, October). The biomechanics of fast bowling in men's cricket: A review. *Journal of Sports Sciences*, 14(5), 403–424. <https://doi.org/10.1080/02640419608727727>
- Callaghan, S., Lockie, R., Andrews, W., Chipchase, R., & Nimphius, S. (2020). The relationship between inertial measurement unit-derived 'force signatures' and ground reaction forces during cricket pace bowling. *Sports Biomechanics*, 19(3), 307–321. <https://doi.org/10.1080/14763141.2018.1465581>
- Constable, M., Wundersitz, D., Bini, R., & Kingsley, M. (2021, September 10). Quantification of the demands of cricket bowling and the relationship to injury risk: A systematic review. *BMC Sports Science, Medicine and Rehabilitation*, 13(1), 109. <https://doi.org/10.1186/s13102-021-00335-8>
- Crewe, H., Campbell, A., Elliott, B., & Alderson, J. (2013). Lumbo-pelvic loading during fast bowling in adolescent cricketers: The influence of bowling speed and technique. *Journal of Sports Sciences*, 31(10), 1082–1090. <https://doi.org/10.1080/02640414.2012.762601>
- Forrest, M. R. L., Hebert, J. J., Scott, B. R., Brini, S., & Dempsey, A. R. (2017, December). Risk factors for non-contact injury in adolescent cricket pace bowlers: A systematic review. *Sports Medicine*, 47(12), 2603–2619. <https://doi.org/10.1007/s40279-017-0778-z>
- Gomez, D., & Rojas, A. (2016, January). An empirical overview of the no free lunch theorem and its effect on real-world machine learning classification. *Neural Computation*, 28(1), 216–228. https://doi.org/10.1162/NECO_a_00793
- Gurchiek, R. D., McGinnis, R. S., Needle, A. R., McBride, J. M., & van Werkhoven, H. (2017). The use of a single inertial sensor to estimate 3-dimensional ground reaction force during accelerative running tasks. *Journal of Biomechanics*, 61, 263–268. <https://doi.org/10.1016/j.jbiomech.2017.07.035>
- Hendry, D., Leadbetter, R., McKee, K., Hopper, L., Wild, C., O'Sullivan, P., Straker, L., & Campbell, A. (2020, January 29). An exploration of machine-learning Estimation of ground reaction force from wearable sensor data. *Sensors (Basel)*, 20(3), 740. <https://doi.org/10.3390/s20030740>
- Hurriem, P. D., Dyson, R., & Hale, T. (2000, December). Simultaneous measurement of back and front foot ground reaction forces during the same delivery stride of the fast-medium bowler. *Journal of Sports Sciences*, 18(12), 993–997. <https://doi.org/10.1080/026404100446793>
- Jacobs, J., Olivier, B., Dawood, M., & NK, P. P. (2021). Prevalence and incidence of injuries among female cricket players: A systematic review and meta-analyses. *JBI Evidence Synthesis*, 20(7), 1741–1790. <https://doi.org/10.11124/JBIES-21-00120>
- Johnson, W. R., Mian, A., Robinson, M. A., Verheul, J., Lloyd, D. G., & Alderson, J. A. (2019). Multidimensional ground reaction forces and moments from a single sacrum mounted accelerometer via deep learning. *Proceedings of the International Society of Biomechanics/American Society of Biomechanics Calgary Annual Conference*, Calgary, AB, Canada. 31 July–4 August 2019.
- Jowitt, H. K., Durussel, J., Brandon, R., & King, M. (2020, April). Auto detecting deliveries in elite cricket fast bowlers using microsensors and machine learning. *Journal of Sports Sciences*, 38(7), 1–6. <https://doi.org/10.1080/02640414.2020.1734308>
- Kautz, T., Groh, B. H., Hannink, J., Jensen, U., Strubberg, H., & Eskofier, B. M. (2017). Activity recognition in beach volleyball using a deep convolutional neural network. *Data Mining and Knowledge Discovery*, 31(6), 1–28. <https://doi.org/10.1007/s10618-017-0495-0>
- Kavanagh, J. J., & Menz, H. B. (2008). Accelerometry: A technique for quantifying movement patterns during walking. *Gait & posture*, 28(1), 1–15. <https://doi.org/10.1016/j.gaitpost.2007.10.010>
- King, M. A., Worthington, P. J., & Ranson, C. A. (2016). Does maximising ball speed in cricket fast bowling necessitate higher ground reaction forces? *Journal of Sports Sciences*, 34(8), 707–712. <https://doi.org/10.1080/02640414.2015.1069375>

- Lafortune, M. A., Lake, M. J., & Hennig, E. M. (1996, December). Differential shock transmission response of the human body to impact severity and lower limb posture. *Journal of Biomechanics*, 29(12), 1531–1537. [https://doi.org/10.1016/S0021-9290\(96\)80004-2](https://doi.org/10.1016/S0021-9290(96)80004-2)
- McGrath, J., Neville, J., Stewart, T., Clinning, H., & Cronin, J. (2021, June). Can an inertial measurement unit (IMU) in combination with machine learning measure fast bowling speed and perceived intensity in cricket? *Journal of Sports Sciences*, 39(12), 1402–1409. <https://doi.org/10.1080/02640414.2021.1876312>
- McGrath, J. W., Neville, J., Stewart, T., Clinning, H., Thomas, B., & Cronin, J. (2022, February). Quantifying cricket fast bowling volume, speed and perceived intensity zone using an apple watch and machine learning. *Journal of Sports Sciences*, 40(3), 323–330. <https://doi.org/10.1080/02640414.2021.1993640>
- McGrath, J. W., Neville, J., Stewart, T., & Cronin, J. (2019, June). Cricket fast bowling detection in a training setting using an inertial measurement unit and machine learning. *Journal of Sports Sciences*, 37(11), 1220–1226. <https://doi.org/10.1080/02640414.2018.1553270>
- McGrath, J. W., Neville, J., Stewart, T., Lamb, M., Alway, P., King, M., & Cronin, J. (2022). The relationship between bowling intensity and ground reaction force in cricket pace bowlers. *Journal of Sports Sciences*, 40(14), 1602–1608. <https://doi.org/10.1080/02640414.2022.2094561>
- McNamara, D. J., Gabbett, T. J., Chapman, P., Naughton, G., & Farhart, P. (2015a, January). The validity of microsensors to automatically detect bowling events and counts in cricket fast bowlers. *International Journal of Sports Physiology & Performance*, 10(1), 71–75. <https://doi.org/10.1123/ijsp.2014-0062>
- McNamara, D. J., Gabbett, T. J., Chapman, P., Naughton, G., & Farhart, P. (2015b, November). Variability of PlayerLoad, bowling velocity, and performance execution in fast bowlers across repeated bowling spells. *International Journal of Sports Physiology & Performance*, 10(8), 1009–1014. <https://doi.org/10.1123/ijsp.2014-0497>
- McNamara, D. J., Gabbett, T. J., & Naughton, G. (2017, March). Assessment of workload and its effects on performance and injury in elite cricket fast bowlers. *Sports Medicine*, 47(3), 503–515. <https://doi.org/10.1007/s40279-016-0588-8>
- Mlakar, M., & Luštrek, M. (2017). Analyzing tennis game through sensor data with machine learning and multi-objective optimization. In *Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers*, Maui, HI, USA.
- Orchard, J. W., Kountouris, A., & Sims, K. (2016). Incidence and prevalence of elite male cricket injuries using updated consensus definitions. *Open Access Journal of Sports Medicine*, 7, 187–194. <https://doi.org/10.2147/OAJSM.S117497>
- Perrett, C., Lamb, P., & Bussey, M. (2020). Is there an association between external workload and lower-back injuries in cricket fast bowlers? A systematic review. *Physical Therapy in Sport*, 41, 71–79. <https://doi.org/10.1016/j.ptsp.2019.11.007>
- Pogson, M., Verheul, J., Robinson, M. A., Vanrenterghem, J., & Lisboa, P. (2020, April). A neural network method to predict task- and step-specific ground reaction force magnitudes from trunk accelerations during running activities. *Medical Engineering & Physics*, 78, 82–89. <https://doi.org/10.1016/j.medengphy.2020.02.002>
- Salter, C. W., Sinclair, P. J., & Portus, M. R. (2007, September). The associations between fast bowling technique and ball release speed: A pilot study of the within-bowler and between-bowler approaches. *Journal of Sports Sciences*, 25(11), 1279–1285. <https://doi.org/10.1080/02640410601096822>
- Senington, B. (2019). *An investigation into the spinal kinematics and lower limb impacts during cricket fast bowling and their association with lower back pain*. Bournemouth University.
- Senington, B., Lee, R. Y., & Williams, J. M. (2018). Ground reaction force, spinal kinematics and their relationship to lower back pain and injury in cricket fast bowling: A review. *Journal of Back and Musculoskeletal Rehabilitation*, 31(4), 671–683. <https://doi.org/10.3233/BMR-170851>
- Simons, C., & Bradshaw, E. J. (2016, February). Do accelerometers mounted on the back provide a good estimate of impact loads in jumping and landing tasks? *Sports Biomechanics*, 15(1), 76–88. <https://doi.org/10.1080/14763141.2015.1123765>

- Stetter, B. J., Ringhof, S., Krafft, F. C., Sell, S., & Stein, T. (2019). Estimation of knee joint forces in Sport movements using wearable sensors and machine learning. *Sensors*, *19*(17), 3690. <https://doi.org/10.3390/s19173690>
- Worthington, P., King, M., & Ranson, C. (2013). The influence of cricket fast bowlers' front leg technique on peak ground reaction forces. *Journal of Sports Sciences*, *31*(4), 434–441. <https://doi.org/10.1080/02640414.2012.736628>
- Wouda, F. J., Giuberti, M., Bellusci, G., Maartens, E., Reenalda, J., Van Beijnum, B.-J. F., & Veltink, P. H. (2018). Estimation of vertical ground reaction forces and sagittal knee kinematics during running using three inertial sensors. *Frontiers in Physiology*, *9*, 218. <https://doi.org/10.3389/fphys.2018.00218>