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Just find it: The Mymo approach to recommend running shoes

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ABSTRACT Wearing inappropriate running shoes may lead to unnecessary injury through continued strain upon the lower extremities; potentially damaging a runner's performance. Many technologies have been developed for accurate shoe recommendation, which centre on running gait analysis. However, these often require supervised use in the laboratory/shop or exhibit too high a cost for personal use. This work addresses the need for a deployable, inexpensive product with the ability to accurately assess running shoe-type recommendation. This was achieved through quantitative analysis of the running gait from 203 individuals through use of a tri-axial accelerometer and tri-axial gyroscope-based wearable (Mymo). In combination with a custom neural network to provide the shoe-type classifications running within the cloud, we experience an accuracy of 94.6% in classifying the correct type of shoe across unseen test data.

INDEX TERMS deep learning, gait analysis, foot pronation, IMU, running shoes.

I. INTRODUCTION

Running is one of the most common forms of exercise due to its ease of access, low cost and beneficial health effects [1, 2]. Moreover, novice and recreational running is becoming increasingly popular and seen as the obvious target for those hoping to encourage greater public health through exercise [3]. In the UK it is driven by the potential of recreational running as a public health promotion target [4]. Indeed, popularity in novice and recreational running has been recently fuelled by the global phenomenon of mass group events [5]. In fact, the latter is perceived to be a useful mechanism for those inclined to be less physical active (i.e. novice), enabling them to better engage with the sport due to the socially orientated-based communities associated with such events.

With a growing number of novice and recreational participant's, rates of running injuries increases with relatively long periods (up to 52 weeks) of injury sustained [6]. This has an obvious economic impact on healthcare utilisation (direct costs) and absenteeism from paid and unpaid work (indirect) [7]. The latter Dutch study examined 1696 participants and found direct and indirect costs per running related injury were up to €71.81 and €54.70, respectively. That can have significant implications for health agencies and employers due to negative impact on public services and loss of productivity, respectively. Additionally, running injuries could cause drop-out from the sport and other activities [6], creating a downward spiral in health outcomes and quality of life. Thus, it is important to gain more insight to the impact of running related injuries and create mechanisms to limit their occurrence.

Most running injuries develop progressively over the many kilometres that are ran, i.e. overuse [8]. However, the aetiology of these injuries is multifactorial [9], implying that to understand the mechanisms leading to an injury, a holistic approach is warranted, including the study of a large set of potential risk factors [8]. The latter study argues that factors could include activities such as training characteristics, running mechanics and anatomy of the runner whereby vertical ground reaction force (VGRF) exerts stress during those activities on bones, muscles and tendons. Thus, as running biomechanics are associated with injury risk, any effect of the shoe type on the running pattern and VGRF parameters deserve attention [8].

Running shoes have experienced tremendous changes in the last 50 years, from very minimal to highly supportive and cushioned shoes and many other variations [10]. Shoes with different functionality have been released because of technological improvements (e.g., material engineering) used in running shoe development, such as cushioned, stability and minimalist running shoes [11]. Currently, there are hundreds of running shoes commercially available for runners with various nuances to entice customers. Yet, guidance for most shoppers is non-existent or limited for their specific needs and requirements. It is important for all runners to be aware of how their foot is balanced [12] as choosing a stability-based running shoe would ease excessive pronation (the degree to which the arch of your foot collapses upon impact), a possible risk factor of running-related injuries [13]. Furthermore, runners often lack evidence-based approaches by disregarding retailer advice (and any in-store technology they may have to aid purchases due to embarrassment or inexperience) and relying solely on consumer trends risk alternating between shoe type and increasing risk of injury [14]. There is a need to enable personalised approaches to identifying correct running shoe type, whereby the customer can collect their own data e.g. in the comfort of their home. This could ensure the customer does not feel stigmatised or pressurised into purchasing too costly a product, unsuitable for their needs.

Wearable technologies are rapidly becoming ubiquitous in our daily lives and viable solutions to provide tailored approaches to healthy living [15] and/or injury prevention from running [16]. Wearables offer discrete, high-resolution data that can be gathered ad-hoc or continuously for prolonged periods for a range of healthcare applications. Inertial sensor-based wearables are perhaps the most common comprising devices such as fitness trackers that quantify movement by measuring acceleration (accelerometers) and angular velocity (gyroscopes). Those sensors are low-cost and can be applied to a plethora of healthcare activities in a range of environments that require quantification of fine motor tasks such as spatial and temporal characteristics of gait [17] for providing objective, personalised data.

Recently, Mymo Group Ltd proposed a Cloud-based approach via a smartphone [18] to provide all runners with better insight to their running mechanics and consequently recommend shoe type to prevent injury. Their platform uses a single low-cost inertial-based wearable to provide a pragmatic solution for all runners that can be used in any setting. Here, we present (i) the analytical methodology that is used to identify features of the inertial signals to examine a runner's gait and (ii) a custom neural network to provide the shoe-type classifications within the Cloud.

The rest of the paper is organized as follows. Section II reviews the underpinning background regarding running analysis and how running shoes are recommended. Section III reports the running shoe recommendation system with 2 typical running gait outcomes. Section IV discusses the wider applicability of the system. Section V concludes the papers and points out future directions.

II. BACKGROUND

A. TRADITIONAL RUNNING ANALYSIS

Video-based assessment is a useful approach to analyse and inspect a runner's gait, such as body alignment and landing position of the feet [19, 20]. That can be a time-consuming process, requiring a trained biomechanics expert to sit and watch the runner from various angles (i.e. front, back, side) to study how their body transitions through space and how the feet make contact with the ground and for how long. Specialist software allows them to study the runner on a frame-by-frame basis with animations to examine joint angles for a complete kinematic analysis. With advances in computer vision and pattern recognition methods, gait assessment can now be automated [21]. Yet, such approaches are computationally intensive and cannot be used at scale given the e.g. requirement for multiple cameras.

B. FOOT STRIKE PATTERNS: Recommending a shoe

Ambulatory and running gait patterns vary from person to person and so each runner requires the optimal shoe to fit their requirements. Typically, a shoe is recommended to an individual based on how the foot lands and makes contact with the ground with patterns divided into (i) pronation, (ii) neutral, and (iii) supination (Fig. 1A). Additionally, foot strike types can also be categorised based on sagittal examination and angle of the foot upon initial contact the ground, (i) heel strike, (ii) mid-foot strike, and (iii) fore foot strike [22]. Depending on the combination of these gait characteristics, a shoe type will be recommended. In general, running shoes are categorised into pronation assisted and neutral support, with pronation assistance often utilising cushioning around the heel to reduce roll [23]. For example, a runner with a mid-neutral profile would receive a neutral shoe type, i.e. stability shoe with gentle arch from front to back. Alternatively, a mid-pronation profile would receive a support shoe, i.e. rigid shoe for increased stability.

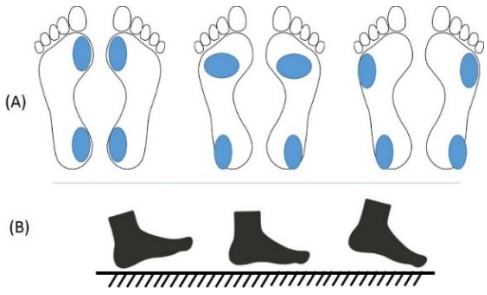

FIGURE 1. Basic representation to highlight feet strikes. From left to right: (A) pronation, neutral, supination; and (B) heel strike, mid foot strike and fore foot strike.

Efforts have been made to utilize wearables to assess foot strike for running shoe recommendation [24]. However, the referenced approach is unsuitable, as it requires the wearable to be attached to the laces of a shoe while running. Given the

runner must use shoes to gather foot strike data, the resulting recommendations may be flawed as the shoes worn during data collection may already provide e.g. cushioning support. Instead, Mymo adopts a bare foot running approach to achieve the most natural measures of a person(s) gait, with a wearable attached via a thin neoprene sock (ensuring firm attachment to the skin and to limit motion artefact, Fig 2) to better understand the natural strike pattern of the foot to recommend shoe type.

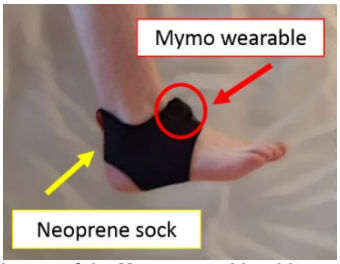

FIGURE 2. Attachment of the Mymo wearable with neoprene sock

III. SHOE RECOMMENDATION SYSTEM

A. SYSTEM ARCHITECTURE

The Mymo infrastructure primarily consists of four modules, Fig. 3. The Mymo wearable is worn on the foot and streams data to a smartphone application (App) via Bluetooth. Once the capture window is over (1min/foot), the App transmits the raw data through an API, where the classification takes place through signal analysis and feature extraction informing a deep learning model, returning the individual's foot strike pattern and their recommended shoe-type.

The environment architecture for time-series analysis and deep-learning model training consisted of a Python 3.7 notebook with an Nvidia K80 GPU backend to greatly increase the speed of training and visualisation tasks. To interface with the Python modules, a Django RESTful API is deployed to a server to listen for data from the mobile application, where analysis and classification take place; allowing the majority of processing to be performed away from relatively low-powered mobile processors.

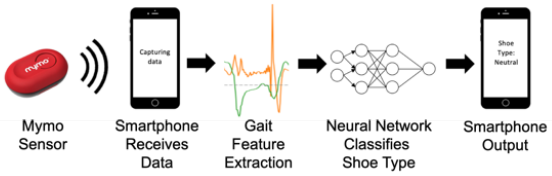

FIGURE 3. Flow of Mymo system from wearable to shoe classification

B. The Mymo WEARABLE

This is a small (37×25×13mm) and lightweight (10g) device, which is worn above the talus joint on the anterior aspect of the left and right foot. It is hypothesised by the manufacturers (Mymo Ltd.) that this location provides the optimal location to determine foot strike pattern (heel, mid, fore) and degree of pronation (neutral, slight, severe). That is because the talus best represents rotations at different stages of the running gait cycle: (i) at heel strike the point of contact between the ground and hindfoot is lateral to the centre of the ankle joint creating a valgus thrust on the subtalar joint, where the calcaneus joint responds by eversion; (ii) that causes the talus to rotate inwardly the talar head to flex plantarly and; (iii) when the forefoot contacts the ground there is a reversal of that motion [25]. The wearable remains in situ on the foot by use of a stretchable neoprene sock (suitable for most foot types) that the runner places on his/her bare foot. A single button on the wearable switches on the device which automatically connects to the mobile App which has a procedure/implementation wizzard for ease of use.

The wearable contains both a tri-axial accelerometer and tri-axial gyroscope, wirelessly transmitting signals to a smartphone (60 Hertz, Hz) during each 1min data capture for each foot, providing approximately 7200 data-points/participant. Before running, the participant is asked to remain (still) in a standing posture for approximately 10 seconds (s) to calibrate inertial sensors to account for individual offsets due to anatomical differences. Once foot strike pattern data is collected for one foot the neoprene sock (with wearable) is removed and placed on the runners other bare foot, to repeat the entire process, including calibration.

C. DATA COLLECTION

Data collection and video capture for Mymo took place over multiple sessions at low-resource (community-based) running clubs and other leisure facilities within the Newcastle-upon-Tyne region, UK. Ethical approval was granted by Northumbria University Research Ethics Committee (Ref: 21603). Adolescent and adult volunteers (n=203, 91M:112F) participated in donning the wearable and gave verbal consent before providing data during treadmill-based testing. All volunteers reported no conditions affecting overall running performance and all were supervised to run on the treadmill for 2mins in total (1min each foot) at a set pace of 5mph/8kph with the Mymo wearable worn on right and left foot.

D. REFERENCE

Video recording with handheld smartphones were used to capture foot strike patterns as the reference standard. Video data (of the runner's waist and legs only) were recorded throughout the duration of testing from front, side and rear views at 120FPS to allow for slow-motion and high-resolution frame-by-frame analysis. Video data were used to identify foot strike and degree of pronation for each runner by a trained physiotherapist and biomechanics expert, who is also an elite club runner. Specifically, he labelled all video data for left and right foot strike type (heel, mid, fore) and degree of pronation (neutral, slight, severe). Subsequently, the expert recommended a shoe type (neutral or support) based on a combination of left and right foot strike parameters. Video data were also use to inform algorithm development for preliminary inertial data interpretation.

E. SIGNAL PROCESSING: Filtering and segmentation

To improve the overall accuracy of the system, data were pre-processed to account for signal noise such as electrical

interference and motion artefact due to any slight size discrepancies of neoprene sock and participants feet.

1) Filtering

A band-pass Butterworth filter [26-28] was applied to account for noise and motion artefact [29]. Performing at 60 Hz with a sampling period of 3 Hz and a cut-off frequency of 5 Hz, we remove extraneous noise from all inertial signals.

2) Dynamic signal segmentation

We define each gait cycle between two periods, stance and swing, where stance refers to the duration of time an individual's foot is on the ground and the contrary for swing [28]. Within the gait cycle are various features often used in gait analysis, the most notable are initial contact (IC) and toe-off (TO) events, which define initial and final contact of the foot with the ground. By locating and quantifying IC/TO events we defined a single cycle of the foot during running.

Utilizing the IC event allowed for the most accurate definition of a gait cycle, as the foot-mounted accelerometer is highly sensitive to contact points; resulting in large, distinguishable regions of interest (ROI) within the signal. By isolating the vertical axis of the accelerometer data we can apply a zero-crossing gradient maxima detection algorithm similar to [30, 31] and successfully isolate the IC events of a signal, Fig. 4. An IC event is only considered if the vertex lies above a dynamic threshold, defined as any point above the 75th percentile range of the smoothed waveform. This will remove abnormal running strides experienced as a runner reaches their terminal speed and help to isolate weak steps if, for example, a runner slightly stumbles. For further robustness, operating within the notion that the average healthy stride is comparable in timing [32, 33], false-positives (IC peaks that are detected too closely together after filtering) can be removed, such that:

$$\left(IC_P < IC_{P+1} - \frac{\overline{x}}{2} \rightarrow IC_{P,valid}\right) \quad (1)$$

where $\overline{x}$ is the average stride length observed by the individual and $IC_{P,valid}$ denotes whether the point is a suitable IC data point.

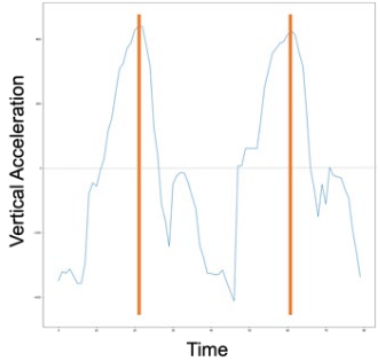

FIGURE 4. A graphical example of how Initial contact (IC) points may be defined by the orange markers

F. RUNNING GAIT OUTCOMES

To accurately classify the correct shoe type for a runner we must consider the features of pronation and foot strike location. Quantifying these features allows for a generalized observation of the gait cycle during foot contact, where pronation predominantly effects the runner.

1) Pronation

Pronation refers to the roll of the foot occurring upon contact with the ground. Thus, IC events were used to evaluate the angle of pronation from the vertical axis and ROI (±30 Hz). Similar to a previous methodology [34], a change-test-repeat approach to define thresholds, where manually changes were made until the best accuracy was achieved on all data in relation to expert raters labelling which was aided by observing the raw data for each participant, Fig 5 and 6. By examining the maximum peaks in the traverse plane about the longitudinal axis within the ROI, we can identify the major roll events around IC, Fig 7. The further the roll peak velocity, the more pronation an individual is considered to experience (neutral ≤0.13s; pronation >0.13s and <0.25s; severe pronation ≥0.25s). This method is applied for every identified IC and an average is taken to account for any occasionally experienced anomalous results.

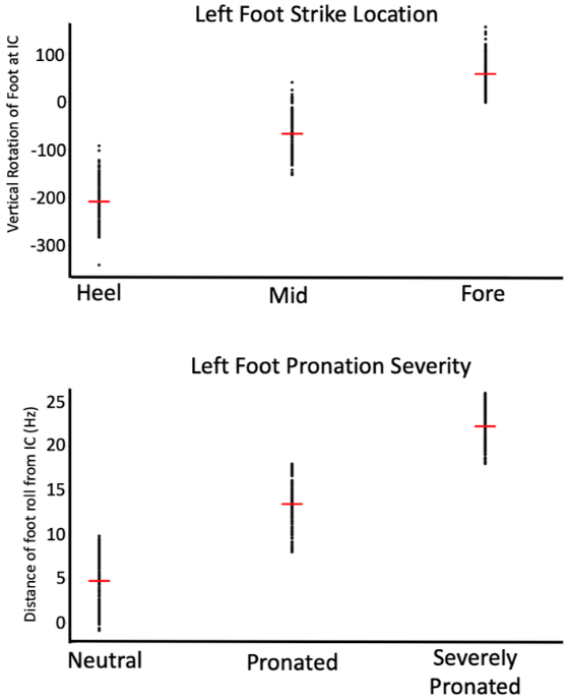

FIGURE 5. Left foot scatter plots strike angles & pronation distances

2) Foot strike

Foot strike location is the angular position of the foot when contact is made with the ground, therefore, to quantify the foot location, one must observe the angle of the foot during IC. Again, the same ROI is used but this time to examine the angular velocity in the sagittal plane about the mediolateral axis to establish the angle of the foot.

G. DEEP LEARNING MODEL: Shoe finder

The results of the feature extraction inform a custom ensemble deep learning model to classify the correct type of

running shoe (neutral or support) based upon the runner's combined left and right foot patterns. We chose to optimise our parameters through random selection based optimisation. The parameters we chose to observe were the number of hidden layers, their respective activation functions, learning rate and the total training epochs. By manually optimising our network parameters, we were able to identify those of the highest effect and eventually land at our final configuration of two hidden layers with relu and *softmax* in each respective layer in combination with 10,000 epochs and a learning rate of 0.2, optimized for maximum performance. The following section describes the data preparation and model structure.

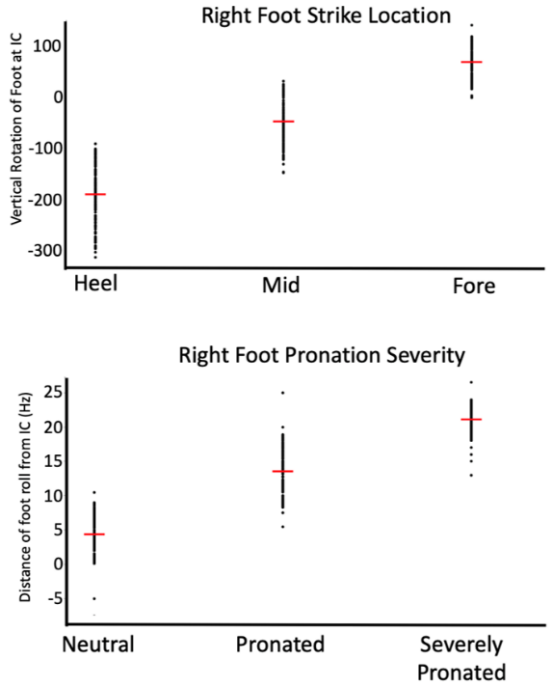

FIGURE 6. **Right foot scatter plots strike angles & pronation distances**

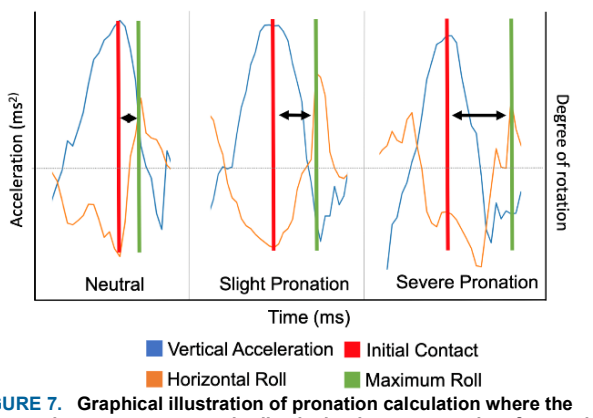

FIGURE 7. **Graphical illustration of pronation calculation where the distance between contact and roll velocity denotes severity of pronation**

1) Data preparation

Participant IMU data were labelled by the expert assessor via video to recommend a shoe-type given severity of pronation and foot-strike location for 203 tests. We split the data into a common and pragmatic 75/25% train-test ratio [35, 36], which provided 51 participant's data for testing the model for evaluating the overall performance. The model takes four inputs, *left pronation (LP), left foot-strike (LFS), right pronation (RP)* and *right foot-strike (RFS)* and has a single output, i.e. shoe type (neutral or support), Fig 8.

2) Model structure

Our final model is comprised of three sub-models; a multilayer perceptron (MLP) classifier [37], a gradient boosted classifier and a custom-trained model; utilised in an ensemble to increase performance. As stated our models hyper-parameters consists of two hidden layers with *relu* and *softmax* activation functions, respectively. Utilising an ensemble model has shown to be effective in optimising the performance of gait recognition and classification [38, 39]. Through calculating the average result of the three models, we are able to account for outliers presented by any given methodology; drastically decreasing false positives in our test data.

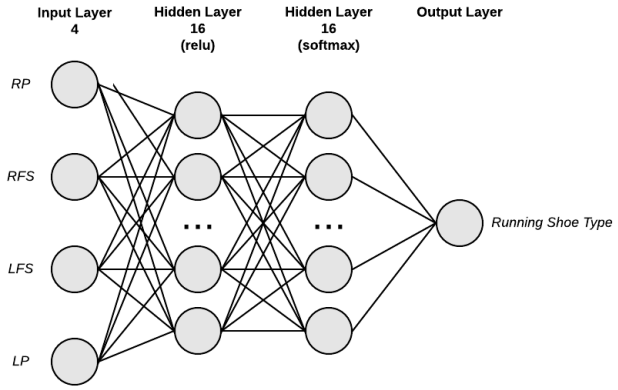

FIGURE 8. **Network structure of custom classifier.**

IV. RESULTS

The following section will describe the final results obtained from each facet of the shoe recommendation system in detail; with the ensemble model's summation and optimisation strategy discussed. All results are evaluated in comparison to manual classification via the video-based reference data.

A. GAIT FEATURES: Pronation and foot strike

Foot pronation and foot-strike location algorithms were tested on all 203 datasets, i.e. the algorithm is static and does not benefit from training data. In comparison to the expert video-based classification, our results concluded with 92.0% and 94.3% for pronation and foot-strike respectively. Those robust foot strike and pronation data were subsequently used to inform the input layer of our neural network.

B. DEEP LEARNING MODELS: Shoe type

During training, our test dataset (51) is utilised to evaluate the performance of each model and benchmarked every 1000 epochs for reference; Fig 9 and 10 illustrate accuracy and loss, respectively.

As seen, each individual network presents reasonable accuracy for shoe recommendation (neutral or support) at

10,000 epochs with the gradient boosting classifier exerting the lowest accuracy of 86.5%, the custom classifier at 90.5% and the MLP classifier at 94%. Upon inspecting these results, it became apparent that in disputed situations, each model may perform differently dependent on their learning biases. Therefore, an ensemble summation of all three tested models is presented in attempt to improve accuracy.

Fig 11 indicates the structural flow of using an ensemble model for running-shoe recommendation. By averaging results of all three models when faced with the same data, we take the average result as our label for shoe-type. Due to shoe recommendation's binary output (1/neutral, 0/support), weightings need not be assigned to any model for bias reduction. Consequently, our final results with the ensemble model amount to 97.7% across all test data.

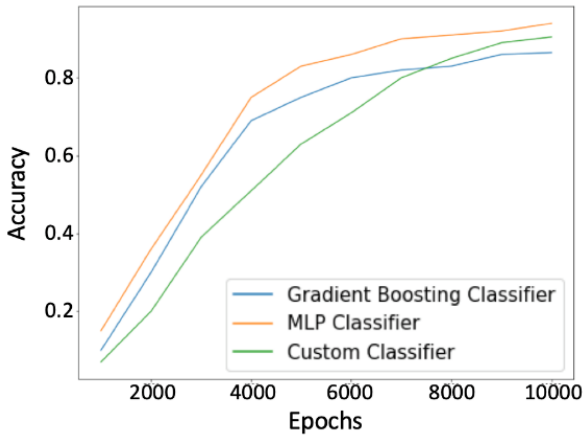

FIGURE 9. Training accuracy of networks used in ensemble model.

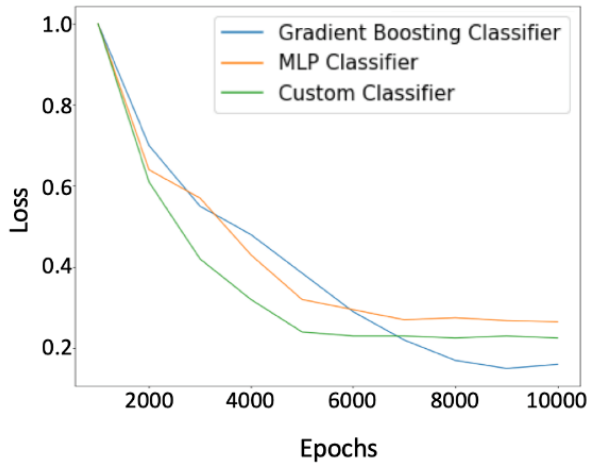

FIGURE 10. Training loss of models in ensemble model.

C. COMPLETE SYSTEM TEST: Gait and shoe type

In full-throughput testing wherein the flow follows the defined Mymo structure of wearable attachment, data capture, gait feature extraction (pronation: neutral, pronation or severe pronation; or foot strike: heel, mid or fore), neural network shoe recommendation (neutral or support), our summated accuracy is 94.6% across all test participants.

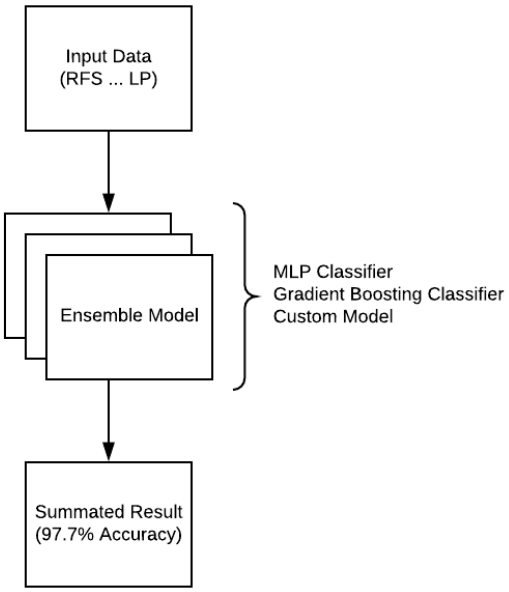

FIGURE 11. Structure of the ensemble model.

V. DISCUSSION

The purpose of this study was to develop a signal processing algorithm for running analysis for use with the Mymo wearable and Cloud-based system. Mymo is a low-cost, commercial device mounted on the foot with the intent of allowing all runners to avoid unnecessary injury through the selection of a suitable shoe. Our approach here will now enable Mymo to quantify pronation (neutral, pronated, severely pronated) and foot-strike (heel, mid, fore, subsequently recommending appropriate running shoe type (neutral or support).

A. SIGNAL PROCESSING

The rate of data smoothing has shown to potentially affect the extraction of foot-strike location and by utilizing different smoothing parameters we can significantly modify the overall result. [40, 41]. To ensure this wouldn't adversely affect the feature extraction, manual adjustment of parameters within the Butterworth band-pass filter were performed until optimal results were achieved. Alternative methods were explored when deciding on the optimal signal processing technique. Our preliminary examination of all data to synchronized videos included moving-average processing to smooth any noise within the data. However, we found the approaches far too aggressive, with significant signal-loss in sensitive domains of the data such as timing of possible IC events, Fig 12. Our final band-pass parameters were a sample period of 3 Hz, a cut-off frequency of 5 Hz and a Nyquist frequency, allowing us to meet an optimal accuracy of 92.0% (pronation) and 94.3% (foot strike) across all testing data.

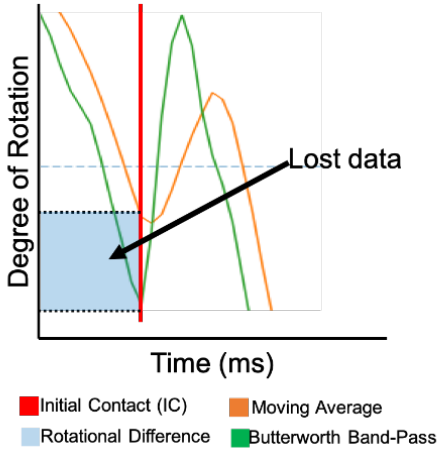

FIGURE 12. Examination of data influenced choice of filter.

B. SIGNAL SEGMENTATION

Zero-crossing approaches to gait signal segmentation have shown to be highly effective across the research domain [42-44]. Here, we adopted the same zero-crossing methodologies within our dynamic signal segmentation to identify IC events within an individual's gait and subsequently located points of interest through isolation of the vertical acceleration. Through utilizing a dynamic threshold based upon the individual's average peak location and height, we were able to successfully differentiate the clearest strikes of the gait cycle; eliminating anomalous strides such as those when a runner begins to reach maximum speed on the treadmill or slows down towards the end of the data-capture period.

Other research has examined the effectiveness of deep learning for signal segmentation, showing the benefit of artificial intelligence which outperforms conventional methods like time series analysis e.g. zero crossing [45, 46]. However, the potential benefit gained through applying neural networks to the dynamic segmentation of high resolution gait data, suffers as a result of the computational complexity associated with their use [47]. Indeed, the approach may not be suitable for a mobile platform, of which Mymo primarily runs.

C. DEEP LEARNING MODEL

Although our features were extracted through conventional data analysis methodologies, those features inform our deep learning ensemble model to classify the correct type of running shoe for an individual. Our initial test results based upon labels assigned from an expert rater was 97.7% across all test subjects.

Accumulative testing of the entire throughput of the system, we were able to obtain an accuracy of 94.6%; proving the effectiveness of the Mymo wearable for classifying running shoe type. Although the final results from the ensemble model were excellent, our test data only consisted of data from 44 participants. Despite this, the test dataset consisted of varied and challenging participants, exhibiting a range of gait kinematics from both neutral and pronated runners.

As previously discussed, neural networks tend to have high computational complexity, posing a concern for mobile deployment. Although our implementation has opted to utilize a neural network for classifying a running shoe type, the average throughput duration is only 1.62s per test, still within a reasonable execution time, which is due to the low dimensionality of our binary classifier. The neural network used here is a low-powered binary classifier based upon the feature-extraction section of our proposed work. The network helps to streamline the process for mobile development due to its low-powered nature. Furthermore, some outliers exist in our labelled data that may not necessarily correspond to a e.g. 'decision tree' approach. Since we require an excellent accuracy, a neural network was suitable to help detect anomalous results and include them in the modelling of output data. If neural networks were to be used for each element of the Mymo infrastructure, execution times will exponentially increase as a neural network would have to endure data containing considerably higher resolution (7200 data points per test) to accurately extract features; with significantly higher computational complexity than the binary classifier used for shoe classification.

1) Practicalities for deep learning on mobile platforms

Similar to dynamic signal segmentation, gait feature extraction has shown to be accurate when applied with deep learning [46]. However, due to utilizing a deep learning model for binary classification of shoe type, overwhelming a mobile device with multiple models for individual tasks may prove to exclude those with older hardware.

D. DATA CAPTURE AND LABELLING

Measuring foot pronation is a highly disputed topic in the bio-mechanic research field [48, 49], with no standardized method for doing so without the use of sophisticated equipment [50]. Although our data capture process included three camera angles and classification from an expert, this process was still technically valid within the confines of foot pronation research. For validation in future work (section V.F), corroboration with gold/reference standard equipment like pressure sensing and/or 3D motion analysis may prove more beneficial for greater running insight and generation of more running features.

E. LIMITATIONS

There is a limitation to the system. The binary output of shoe recommendation (i.e. neutral or support) excludes the ability to differentiate supination from neutral observing runners. As our approach measures the distance between IC and maximum roll, supination classifications are considered as neutral due to an opposite roll direction from those experiencing pronation. Although this presents a limitation to the labelling of a runners' pronation severity, major manufacturers recommend a neutral cushioned running shoe for those experiencing supination [51, 52]; and as such, will not affect the overall recommendation of running shoe to the end-user.

F. FUTURE WORK

Here, we present a methodology for 2 useful running gait outcomes for use on the Mymo system. Pronation and foot strike have been useful to inform a running shoe with excellent accuracy. Next we aim to quantify and validate additional outcomes such foot contact time with the ground to 3D motion analysis in a laboratory setting. It is hypothesized that additional outcomes will better inform the Mymo system for improved runner analysis. Moreover, we will expand shoe classification methodology to "neutral with support" to aid classification of runners with supination.

Our model selection and hyper-parameter optimization followed trial-and-error procedures, with the highest performing model configurations applied to the final ensemble model structure to achieve the aforementioned accuracy rates. In future work, streamlining the process through the application of an autonomous training algorithm such as Particle Swarm Optimization [53] may prove useful. Such approaches provide an evolutionary method to maximizing the accuracy of a network; by training models and assessing the test accuracy over multiple iterations, we are able to hand-select the best configuration established by the process. Other approaches may also be taken in a similar domain such as an automatic random grid-search [54] and a genetic algorithm approach [55].

VI. CONCLUSION

The Mymo wearable is a low-cost product, providing shoe recommendation for runners with the use of an inertial sensor mounted on the foot. This paper presents a novel approach for the recommendation of running shoe type through the use of time-series gait feature extraction techniques to inform a custom deep learning ensemble model for running shoe recommendation; with a combined accuracy of 94.6%.

Future work will explore the feasibility of using neural networks for feature extraction as well as classification in an attempt to further improve accuracy while maintaining efficiency. Extraction of different gait parameters may also help to inform running information for all individuals while developing the Mymo system.

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