Pose Estimation and Machine Learning for Sprinter Form Comparisons

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Abstract

Our study aims to discover what joints and other factors play the most important role in developing faster sprinters. Using data from high schoolers and professional athletes, differences were compared in each athlete's top speed position at their MVP stance, which is the maximal height of vertical projection as defined by the ALTIS Kinogram Method. With TensorFlow's MoveNet Thunder pose estimation model, each athlete's leg and arm limb angles were investigated. Alongside these angle key points, the ground-to-air ratios (number of frames with foot on the ground divided by number of frames with foot in the air) of each athlete at their top speed were measured. Comparing the angles, it was discovered that professional athletes tend to have a more constricted range of movement at their maximal height projection. In comparison, school athletes tended to swing wider in the same position. With speed data of the high school athletes, it was also found that a shorter ground-to-air ratio also meant a typically faster time. Paired with this data, models also determined that the front hip and elbows determine athletes' speed. However, while these findings may serve as benchmarks for success, performance will vary among athletes, so individualized training will most benefit a sprinter.

1. Introduction

Previous research has identified critical components of sprinting mechanics that contribute to overall performance. Mann's and Herman's (1985) study on a 200-meter dash provided insight on the fundamentals of biomechanical skill, stating in their study that "the critical body kinematics variables related to success included upper leg angle at takeoff (indirect), upper leg velocity during support (direct), lower leg velocity at touchdown (direct), foot to body touchdown distance (indirect), and relative foot velocity at touchdown" (Mann and Herman). Similar to this study, Hunter, Marshall, and McNair (2005) conducted research on twenty-eight male athletes, collecting video and ground reaction data. Their study found that "variables describing horizontal velocity of the body's center of mass were the most reliable, whereas variables based on vertical displacement of the body's center of mass or braking ground reaction force were the least reliable" (Hunter et al.), emphasizing velocity over body positions. Weyand et al. (2000) investigated step frequency and contact time, concluding "human runners reach faster top speeds not by repositioning their limbs more rapidly in the air, but by applying greater support forces to the ground" (Weyand et al.). These studies underscore the complexity of sprint performance and suggest that a combination of biomechanical factors influences an athlete's ability to achieve maximal speed.

One can adapt their techniques to achieve greatness or follow in the footsteps of greats before them. In sprinting, the emphatic trend to becoming the fastest runner is looking towards the best, like Usain Bolt, Asafa Powell, or Tyson Gay. This study aims to explore what makes these athletes so great, to find the relationships between sprinting angles, ground-to-air contact ratios, and sprinting speed in both high-school and professional level athletes. Pose estimation has been a tool used by developers over the past few years to analyze human movement through footage. This study uses pose estimation to analyze limb angles, and paired with ground-to-air ratio data, is compared to speed data of high-school athletes with the objective of identifying biomechanical and ground-contact trends that distinguish the fast and slow.

2. Methodology

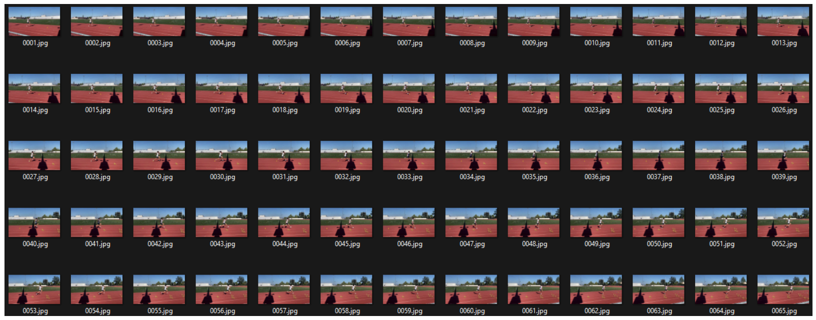
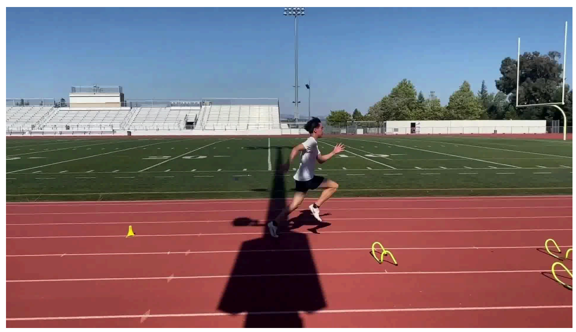
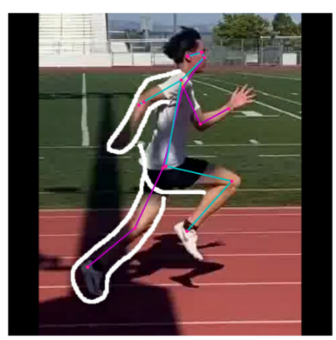
2.1. Data Collection

Data collection and analysis took a straightforward approach: collect data from videos, splice and edit the videos into images manually, run the images through code, and analyze the results. The most crucial part of understanding the biomechanics of a sprinter through image analysis is finding footage to supplement data analysis. This footage ranged from videos on the internet to training data from my high school's track and field team's workouts. These videos were then downloaded and uploaded into a video-to-image converter, numbered each frame, which was a minor but crucial detail for later analysis. Each frame was then analyzed to check whether the athlete's position matched those in the ALTIS Kinogram method, specifically the MVP, which is "the maximal height of vertical projection, as defined by the position where both feet are parallel to the ground" (McMillan). These images were then cropped and painted over manually using digital software for the pose estimation model to analyze body positions better. TensorFlow's MoveNet Thunder pose estimation model was used to analyze images as it is a relatively quick, accurate, and easy-to-set-up model. With TensorFlow, multiple body angles deemed essential in sprinting were captured, including the pull of the back leg, the knee-rise at max velocity, and the forward-lean overall. Along with capturing body angles, it was determined that a crucial part of sprinting is ground-to-air contact time, as the time spent between the ground and air plays a significant role in how power is effectively applied during sprinting. For example, a jogger spends much of their time running with their feet on the ground as they are not focused on applying excessive power to the floor, and a person walking spends the entire time with at least one foot on the ground. Conversely, in sprinting, athletes are encouraged to apply vertical force into the ground, propelling themselves forward and upwards. A more extreme example would even be jumping, as one would hope that most of the time spent by an athlete participating in the long jump would be in the air. We hoped to locate trends in faster sprinters by using ground-to-air contact time ratios and the body angles captured during the ALTIS Kinogram phases.

Table 1
Metrics at MVP analyzed with Tensorflow MoveNet

Metric	Knee	Hip	Shoulder	Elbow
Description	Knee angle measured from hip to knee vertex to heel	The hip angle measured from shoulder to hip vertex to knee	Shoulder angle measured from elbow to shoulder vertex to hip	Elbow angle measured from wrist to elbow vertex to shoulder

Table 2
Data collection process

1. Video footage is collected and spliced into individual frames.	
2. Frames are sorted and picked out individually to be analyzed; simultaneously, the number of frames is saved to the data.	
3. Frames are cropped and any obstructions are painted out to help the model better identify joints.	
4. The model analyzes the image and captures body angles; the ratio between ground and air is also calculated with the model.	

5. Data is entered and organized onto a spreadsheet for analysis.

	athlete	position	left hip	left knee	right hip	right knee	left shoulder	left elbow	right shoulder	right elbow	upper tilt
0	aidan	left full support	174.621873	167.009355	164.314643	163.840651	2.903313	162.275867	11.519275	160.055976	10.129590
1	aidan	left mvp	124.257640	131.846160	120.422056	129.044369	45.393062	162.290396	19.135719	83.563621	2.017854
2	aidan	loop	173.950297	172.653256	175.581991	176.147364	10.509098	168.344973	20.179440	152.796960	10.090397
3	aidan	left strike	122.178034	147.737234	134.213952	161.398830	32.030957	164.233104	29.843871	154.813520	1.968534
4	aidan	left touchdown	151.274699	155.885306	146.193262	156.991713	6.862589	169.865334	16.996734	147.977735	5.025253
...	...	...	...	...	...	...	...	...	...	...	...
4279	tevin2	NaN	144.080174	153.003421	161.912383	161.440180	9.741346	160.062410	4.120824	174.009600	175.441697
4280	tevin2	NaN	169.622526	168.420398	179.829504	167.587415	2.596759	161.641811	0.903582	149.461421	179.483180
4281	tevin2	NaN	175.845529	177.393281	178.979653	171.909169	4.029908	169.498711	3.398688	125.798760	179.164939
4282	tevin2	NaN	175.813103	170.248243	167.756958	160.107096	18.799178	147.922408	16.385713	153.079879	178.508285
4283	tevin2	NaN	178.423920	178.187218	178.765586	170.631915	7.091516	158.150440	0.266456	153.358492	4.909203

3. Results

3.1. Exploratory Data Analysis

After data was collected and organized, amateur and professional athlete graphs were constructed using Python.

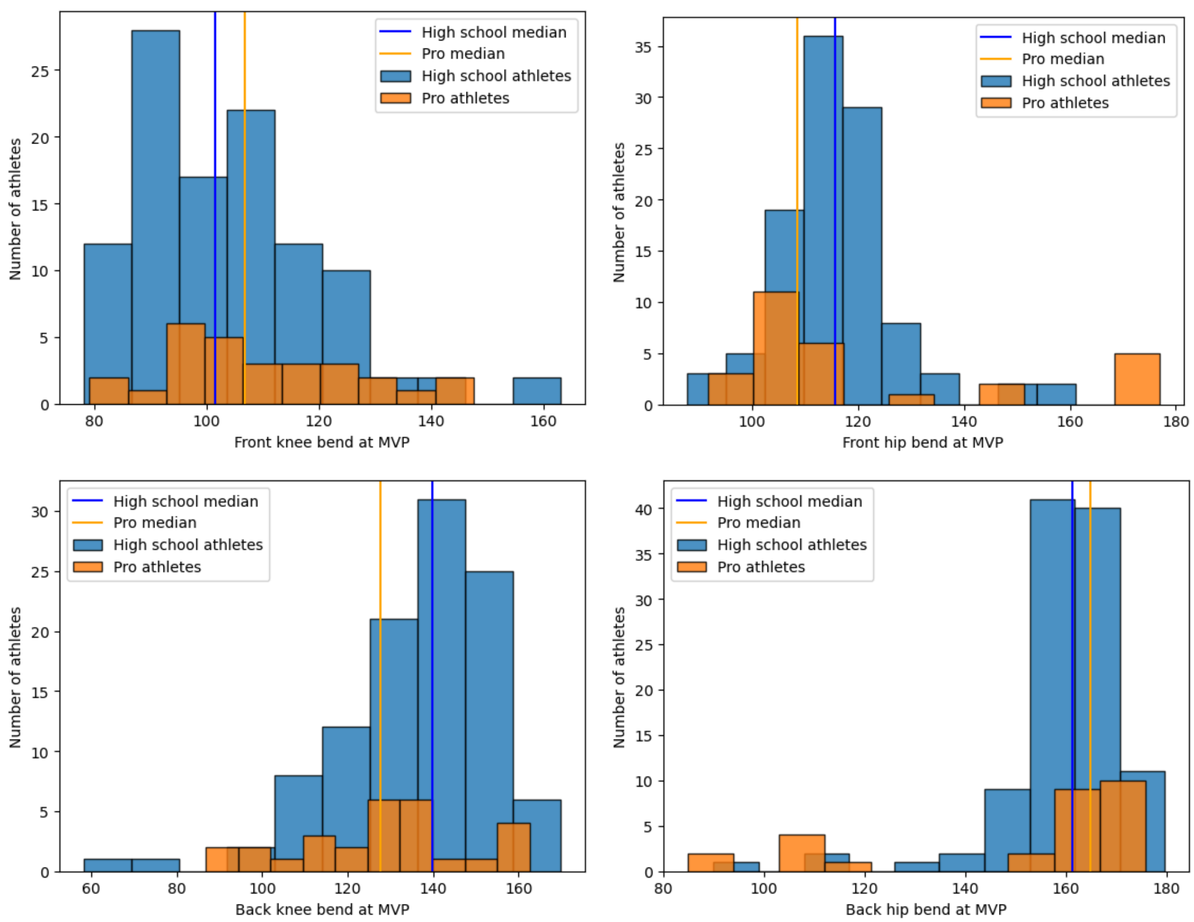


Fig. 1. Histograms displaying the distribution of front and back hip and knee bends at MVP position. Data compiled from various online video analyses (see References for details).

When comparing the angles of the front knee bend at the top sprinting position between the professional athletes (orange) and amateur athletes (blue), it was discovered that, as expected, normal, more amateur athletes would exhibit a wider variety of angles compared to the professional athletes. While professional athletes still showed a wide range of angles, the identified range was slightly shorter and converged near 100 degrees, even with a low sample size. On the other hand, the angles of the amateur athletes centered around 90 degrees and 110 degrees, showing inconsistency in the athletes. Some notable outliers exist in all graphs due to a discrepancy in TensorFlow's MoveNet model, which sometimes may mix up the left and right sides of the body due to an unclear image. Ignoring the values to the right, which are determined to be discrepancies with the model's code, there is an even clearer difference in terms of the front hip bend between high school level and professional athletes, with pro athletes exhibiting a much lower bend in general, which can likely be explained with the fact that professional athletes will tend to be able to lift their leg higher at their top position, exhibiting a lower hip angle. Even when observing the angles of the back knees and hips (ignoring the discrepancies), professional athletes, at the very least, tend to have a lower average back knee and a higher average back hip angle.

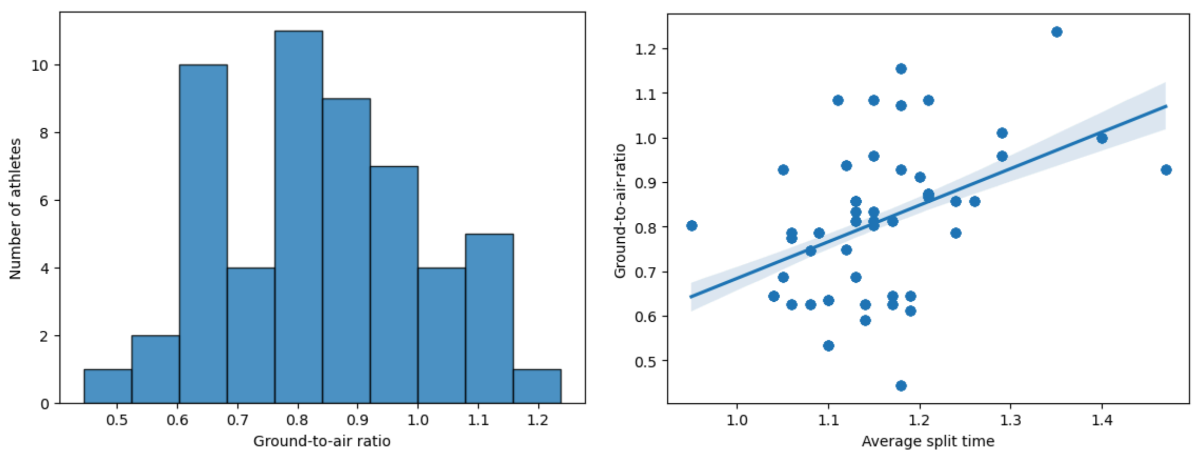


Fig. 2. Histogram of distribution of ground-to-air ratios of high school sprinters accompanied with linear regression plot of average split times to ground-to-air ratios of high schoolers

Looking at the ground-to-air ratios of high school athletes, a wide range of values exists, ranging from 0.5 to 1.2 but ultimately centering around 0.8, which is the typical ground-to-air ratio spent for a high school sprinter. When comparing the split times of a 10-meter fly during the workout in which the ground-to-air ratio samples were also taken for each recorded athlete, there is a positive linear correlation between ground-to-air ratios and split times. The lower the split time, the generally lower the ground-to-air ratio, and this logic would follow sprint mechanics scientifically as it has been proven that less time spent on the ground equates to faster speed in general. There will be discrepancies as power and form play a prominent role in determining speed, but generally quicker people with better form are more likely to spend less time on the ground.

3.2. Modeling

Modeling was the last and most crucial step in determining what defines a good sprinter. For the test-train split, a 25:75 ratio better fits our needs for an evaluation model. The sample size of our data is relatively small, containing about 50 key points, and the 25:75 split is a standard and flexible ratio to test with. The dependent variable was the average split time for each athlete, and the independent variables were all the angles associated with each split time that was unique to each athlete.

Regarding running models, three models were chosen, each with relatively similar accuracies. The first model was multiple linear regression, which compared all the key points in a low-dimensional analysis. It was most straightforward to understand and compare, and it seemed most logical given the assumption that there were likely direct relationships between faster times and specific angles that needed to be exhibited –such as a higher knee lift– when sprinting. The second model was the random forest regressor, a learning method that builds multiple decision trees and combines their outputs. To account for the still possible non-linearity of data between split times and angles, the random forest regressor was used as it is resistant to overfitting and effective against high dimensionality, which is also a problem that could have been encountered: there are many angles to reference from, the front hip, the front shoulder, the front knee, etc. The last model was an XGBoost regressor, which uses gradient-boosting to predict highly non-linear relationships. This was most effective for our dataset as our data contained many features and points that had to be compared. Overall, it is a great model in terms of flexibility and accuracy. However, when comparing all the mean absolute and mean squared errors, the XGBoost regressor surprisingly did the worst, albeit only slightly. All three models fell within roughly the identical scores, each having an absolute error of approximately 0.055 and a squared error of 0.0045, with the XGBoost regressor model being an exception with a squared error of around 0.0057.

Table 3
Mean-absolute-errors and mean-squared-errors of multiple linear, random forest, and XGBoost regression models, respectively

Model	MAE	MSE
Multiple Linear Regression	0.05765267356793944	0.004356423303205583
Random Forest Regression	0.05464999999999994	0.004486323333333466
XGBoost Regression	0.055812061627705876	0.0057454938633964905

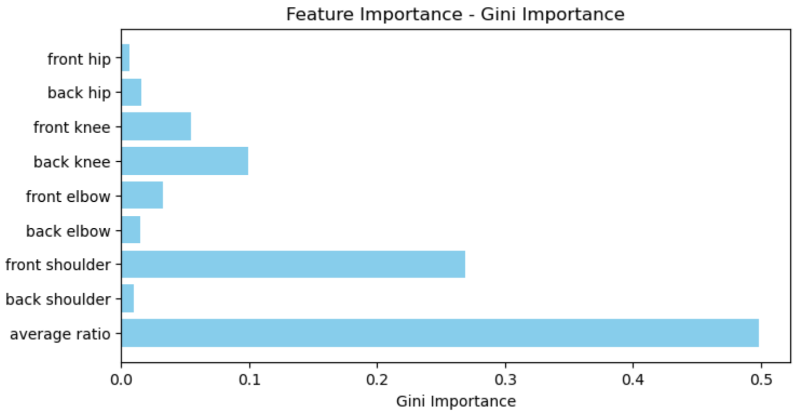


Fig. 3. Feature importance lists of angle and ratio metrics versus average split times for Random Forest model

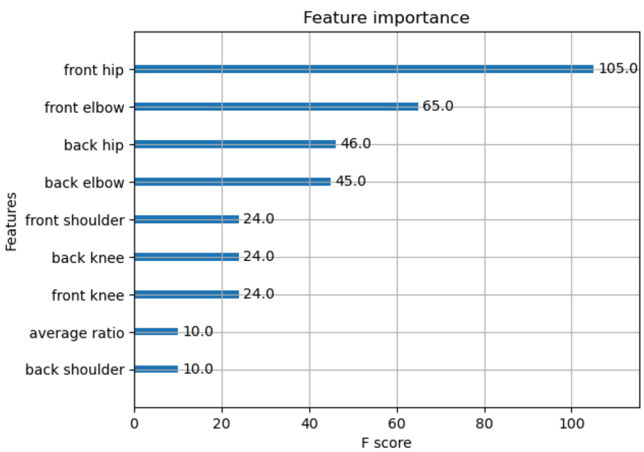


Fig. 4. Feature importance lists of angle and ratio metrics versus average split times for XGBoost model

4. Discussion

Observing the histograms from the exploratory data analysis (see Fig. 1), professional athletes, from the front of the body during MVP positioning, tend to do a much better job at pushing vertical forces down through the knee with a 90˚ angle, and they also can keep the leg high with a lower hip angle. Regarding backside mechanics, professional athletes do a much better job at positioning themselves to cycle the leg, keeping a low knee bend and higher hip bend to bring the leg forward quicker. Using the median angles of both high school and professional athletes as a reference, when visualized, professional athletes tend to maintain a tighter, constricted form at maximal height projection, which is an emphasized quality of good sprinters. Maintaining tighter angles means that faster turnover occurs as it is easier to bring the foot down.

Using the scatterplot of the ground-to-air ratios versus average split times (see Fig. 2), we observe a trend that is emphasized by sprinting coaches and researchers. As mentioned, lower time spent on the ground—a lower ground-to-air ratio—means that times will also be lower. This occurs because the faster a sprinter can apply vertical force into the ground, the faster they will be able to run.

The feature importance lists between the random forest regressor (see Fig. 3) and the XGBoost regressor (see Fig. 4) differed significantly in the emphasis on what aspects of sprinting they used. While the random forest model favored the average ground-to-air ratio and front shoulder metrics the most, the XGBoost regressor preferred using the front hip and front elbow as its top metrics. The algorithmic difference between each model accounts for their differences in higher-scoring metrics. The random forest model favors the broader metric, the average ratio, likely because it has a more linear relationship with the average split times of runners. Referencing the previous linear regression plot of the average ratios and divided times, a linear correlation can be seen, and this is likely also what the model recognized. The XGBoost model determines that the front hips and elbows are more critical in deciding sprinting speed. The emphasis on these front angles can also be because the front hip angles generally are more constricted to about a 90˚ angle when sprinting. Most sprinters will bend their hips around this range, and this explanation can also account for how the front elbow functions, as its angles and movements reflect the leg movements and are also somewhat constricted. The knee angles, however, did not score very highly in either model. A likely cause of this is that knee extension when sprinting can vary from athlete to athlete. Unlike the hips, there can be a more extensive range of extension, such as over-striding or not bending the knee enough, which can lead to various angles.

5. Conclusion

We ultimately concluded that many factors play into an athlete's success in sprinting. Still, most importantly, the factors most emphasized in coaching, the hips, remain the most important in making an athlete faster. Certain angles, like a 110˚ bend at the front hip, are also more typically exhibited, serving as a benchmark for athletes to display. However, working solely on the hips will not make an athlete faster. Every joint plays a crucial role in developing vertical force, ground-to-air times, and overall speed. Many surprising results came from this project, and there could have been more accurate predictions given more data points and evidence, especially professional split times and videos. These 50 points serve as a simple baseline, emphasizing the importance of certain features of sprinting but also emphasizing that there will always be variance among athletes. While it may be helpful, it is unnecessary to constantly focus on hitting the most common angles or reaching the fastest ground-to-air times. This project aimed to show what was most commonly exhibited and emphasized to help the fastest be the fastest, but these tendencies will not be displayed in everybody. Coaches will always emphasize on race day to get out there and go as fast as possible. The fastest, truest sprinters will step up to their race, take a deep breath, and run.

This study contained a small dataset, which, with more points, could provide more accurate results. More concrete results can be produced by either scouring the internet for clear racing footage or recording data of athletes by oneself. In terms of video footage, slow-motion recordings would be more useful in both determining the MVP position as described and calculating more accurate ground-to-air time ratios. A majority of the data collection process was manual, and automating the process of splicing footage and identifying the MVP position would greatly improve the convenience in continuing this study. By addressing these limitations, future research can provide deeper insights into sprint mechanics and pave the way for more effective training methodologies.

6. References

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