Developing Analytical Tools to Impact U.Va. Football Performance

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***Abstract* - Data analytics has permeated the sports world, but the funds needed to employ data scientists dedicated exclusively to programs at the collegiate level are hard to come by. As a result, Division I football programs are currently not using data analytics and technology to their full potential. This project aims to use technology and data analytics to enhance the performance of the University of Virginia Football program and serves as a continuation of the efforts of previous U.Va. Systems Engineers to bring U.Va.'s program to the technological forefront of college programs. This paper outlines ongoing efforts involving supplementation to analyses currently being done by the program while also introducing new methods to aid the U.Va. coaching staff. Building upon the previously identified "Three Pillars of Data Analytics" for U.Va. Football, this multi-faceted project includes an analysis of how players' practice performance corresponds to in-game performance, the validation of a previously built 4th down decision tool delivered last year as a means to aid in difficult in-game decision making, and the development of an automated tool to classify offensive play formations using computer vision. These efforts aim to help the coaching staff optimize practice schedules, provide them with data-driven decision-making aids to be used in-game, and increase opponent scouting capabilities while also saving the labor required to do so.**

Index Terms - Logit Model, Computer Vision, Player Tracking, Hough Transform

INTRODUCTION

Modern sports teams are looking for whatever competitive advantages they can gain in order to stay on top of their opponents, as demonstrated by the increased implementation of technology into the sports world. From Major League Baseball to the National Basketball Association, professional programs have demonstrated that data analytics can be utilized to implement effective strategies to enhance performance both on and off the field, but significant breakthroughs have yet to be realized in football. In particular, college football programs as a whole are much more limited in resources and cannot afford to place as large an emphasis on spending money on data analytics. In an ESPN survey to all sixty-five Power-5 conference football teams, only seventeen of the sixty-five teams responded and admitted they were invested in some form of data analytics, whether it be an entire department or a single person [1]. One respondent to the poll said that the top programs in the country are probably reaching the analytics load of pro teams, but that "the vast majority of [teams] are trying to figure out how to pay for meals and travel, or the hire of an extra recruiting assistant or athletic trainer, especially as budget cuts continue to affect the public colleges and universities" [1].

The University of Virginia Football team has started to build data analytics into the program's operations, however, they don't have the funds to hire permanent data scientists. Therefore, they have turned to the University's Department of Systems and Information Engineering to explore higher levels of integration of data analytics into their program. This multi-faceted project contains three primary analyses, including how the football team makes fourth down decisions, how practice data can contribute to performance, and a proof of concept to streamline the scouting process on a week to week basis.

LITERATURE REVIEW

This project serves as a continuation of the research from previous systems engineers, and thus uses their identified "Three Pillars" as a foundation for continued work [2]. The analysis of fourth down decision making relies on a state of the game model built by Elkins et. al. The player performance model was motivated by other U.Va. athletic programs and how they use data to assess performance in training and plan for game preparedness, such as a report provided by U.Va. Women's Field Hockey Coach Rachel Dawson.

Developing a proof of concept for generating scouting report data using computer vision was this team's approach to addressing the third pillar. This was motivated by the work of Atmosukarto et. al, which attempted a similar task four years ago and serves as a baseline for the approach used [3]. Additional foundations for working to classify formations were provided by the work of Timothy Lee in [4]. However, the use of color without constructing a mosaic of the field proved less scalable in preliminary iterations, as team colors will commonly match on-field logos.

THE THREE PILLARS

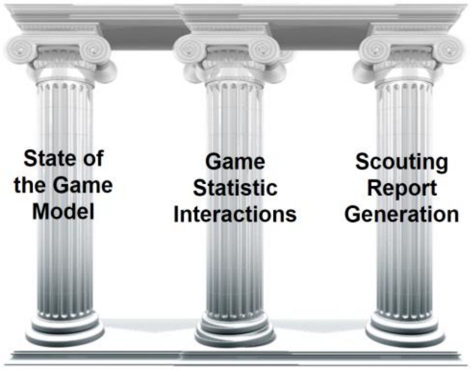

FIGURE I
THE THREE PILLARS OF DATA ANALYTICS GENERATED FOR U.VA. FOOTBALL

I. Fourth Down Decision Analysis

In-game play selection for football teams is typically conducted by a team's head coach or offensive/defensive coordinators rather than the players on the field. General play calling can sometimes be obvious depending on the current state of the game (e.g. Punting on 4th and 10), however, most play calls throughout the game are subjective and no optimal decision is obvious (e.g. Punting or going for it on 4th and 1). Previous work conducted by Elkins et al. aimed to aid the U.Va. coaching staff's decision making process by developing a "State of the Game" model based on all college football play-by-play data from 2005-2013 to increase the objectiveness of in-game decisions [2].

This "State of the Game" model was designed to estimate a team's win probability with over 99% accuracy determined by a logistic regression model [2]. The tool inputs parameters for current down, distance to the first down, field position, score differential, Las Vegas spread line, and time remaining. It then outputs the probability of winning the football game. By examining the current game state and potential state transitions that can occur in the next play, the model can provide the coaching staff with insights about the risks/rewards of passing, running, punting, kicking a field goal (FG), accepting penalties, and going for it on fourth down. The win probability model was applied to create a Fourth Down Decision tool, which determines using historical data the optimal decision of electing to punt, kick a field goal, or 'go for it' (GFI) on fourth down given the current state of the game. Its potential value warranted further investigation of the usefulness of the decision-making tool and assessment of how often the U.Va. coaches opted to agree or disagree with the model's recommendations.

The Fourth Down Decision Tool cannot be used in-game as Division I Football rules state that computers "are not allowed in the team area, on the playing field, or on the sideline" unlike the National Football League (NFL), and therefore decision making by the coaches must be communicated on the fly or evaluated in the previous week's preparation [5]. U.Va. coaches are, however, allowed to print documents before the game and use them throughout. An Excel spreadsheet tool was thus developed by Elkins et al. to allow the coaching staff to input spread, time, and kicker strength data (max field goal distance, max punt distance) and receive printable sensitivity analyses visualizations from the Fourth Down Decision Tool for upcoming games [2].

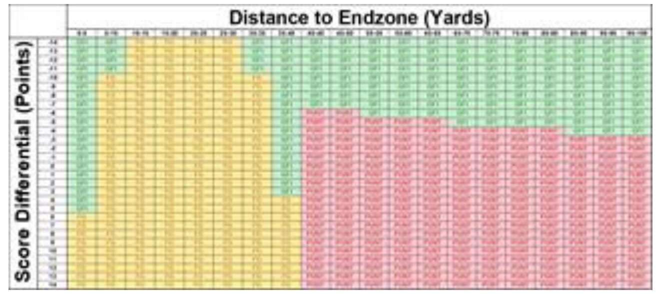

FIGURE II
FOURTH DOWN DECISION TABLE

Figure II displays a sample Excel sheet created by the Fourth Down Decision Tool based on a unique game state. Green represents "go for it," yellow represents "kick a FG," and red represents "punt." The columns are navigable by current score differential and distance to end zone. The recommended decisions within each cell update as the state of the game inputs are changed to indicate updates in the tool's recommended decision.

Analysis of the coaching staff's fourth down decisions involved first gathering all data from U.Va.'s fourth down plays in the 2017 season, which included all aforementioned game state fields, the model's recommendation, the actual play call, the resulting game state, and the changes in projected win probability. By finding the difference between the model-recommended play's win probability and the actual play's win probability, it was possible to identify situations in which the coaching staff potentially failed to make the optimal play call based on the win probability model.

While this fourth down decision analysis aims to be insightful for the coaching staff, it must be acknowledged that some amount of error exists within the model. It cannot completely account for subjective in-game factors that coaches understand such as injuries, weather, momentum, and overall understanding of players' abilities. Nevertheless, the model does suggest the most historically effective decision, supported by the data from all fourth down plays from 2005-2013.

The U.Va. Football team had 118 fourth downs this past season, and of those 118 instances, the coaching staff followed the model's recommended decision 93 times, which is a rate of 78.8%.

There are many situational factors in which decision making did not significantly deviate from this rate, such as quarter. Analyzing U.Va.'s fourth down decision making by each quarter in Table I showed little insight, indicating that this was a measure not further worth investigating.

TABLE I
2017-2018 SEASON FOLLOWING MODEL BY QUARTER

Quarter	No	Yes	Total	Rate
1	5	23	28	82.1%
2	8	28	36	77.8%
3	6	17	23	73.9%
4	6	25	31	80.6%
Total	25	93	118	78.8%

However, it can be seen in Table II that the coaching staff actually tended to disagree with recommended field goals 55.6% of the time (No = model not followed, Yes = model followed), and typically elected to "go for it" instead. The often subjective decision of kicking a field goal or going for a first down can be viewed as a measure of conservativeness for a head coach and these analyses can be helpful for evaluating the effectiveness of decisions made in previous games.

TABLE II
2017-2018 SEASON FOLLOWING MODEL BY RECOMMENDED PLAY

Rec. Play	No	Yes
Punt	6.6%	93.4%
Go for it	41.7%	58.3%
Field goal	55.6%	44.4%
Total	21.2%	78.8%

Table III examines how closely the team followed the model by field position. It is notable how coaches' fourth down decision making deviates more from the tool as the U.Va. offense moved closer to the end zone. Understandably, the team almost always followed the tool beyond 35 yards because this is near the threshold where field goals become too difficult and where a turnover would lend excellent field position to the opponent. Though the sample size is small, the offense actually overlooked the tool more often than not while within the red zone (within 20 yards), and only followed the model 50% of the time within field goal range (within ~35 yards). Although the goal of the tool is not to overrule play call decision for the coaching staff, its informative input is useful for supplementing decision making and can act as a possible "sanity check" for tough calls. One significant call per game will not change the scope of an entire season, but aggregating small added win probabilities over time could lead to an added expected win over the course of multiple seasons.

TABLE III
2017-2018 SEASON FOLLOWING MODEL BY DISTANCE TO END ZONE

Yard Line	No	Yes	Total	Rate
0-5	3	2	5	40.0%
5-20	5	5	10	50.0%
21-35	8	9	17	52.9%
36-50	3	19	22	86.4%
51-100	7	56	63	88.9%

Future applications of the model could focus on more in-depth situational analysis in addition to validation of the tool's outputs. This could include scraping data for more Division I teams and evaluating if they followed the model more closely and if more objective decision making on fourth downs allowed them to outperform expectations set by analysts prior to the season. Another possible iteration of the Fourth Down Table could be created in which the 'weight' of a decision is indicated, such that strongly recommended plays (expected added win probability for a given play is greater than ~2%) are highlighted differently. Additionally, the model can be tailored to utilize data on U.Va.'s kicking and punting outcomes rather than historical outcomes, as the personnel that U.Va. has on hand increases the subjectivity of fourth down decisions.

II. Player Performance Model

To improve the overall performance of a football team, it is imperative for coaches to track and evaluate the individual performance of their players. Most college football teams, including U.Va. utilize a grading system to assess the performance of their players during games. This grading system allows teams to quantify their players' progress over time and make important decisions regarding practice and training regimens. U.Va. currently uses a binary grading system on each play a player is in the game, which though insightful, can be highly subjective based on opponent skill and coaches' expectations. To supplement this grading system, grades per U.Va. player were acquired from Pro Football Focus (PFF), a company that gathers extensive data from each FBS game. These grades are consistent and readily available and therefore used as the metric for performance in the model. The goal for this portion of the project was to create a model that would allow the U.Va. Football team to maximize the performance of their players during each game.

The main predictor variable chosen for data collection was "practice load," which is generated through the Catapult wearable vests used in practice. Each Catapult vest includes numerous sensors to record data. For example, accelerometers and magnetometers track exertion during practice by measuring distance traveled, bursts of acceleration, top speeds reached, and a cumulative "load" exerted during the session. "Practice load" was selected as the metric of focus as it was expected to have the most direct impact on game performance due to player conditioning. One pursued hypothesis attempted to correlate excessive practice during the week before the game with a decrease in game performance due to fatigue. Likewise, another hypothesis attempted to correlate low practice load the week before with a decrease in game performance due to the lack of practice.

Utilizing the Catapult data from the 2017 season, graphs were generated to display the relationship between practice load and game grade for specific players, shown in Figure III.

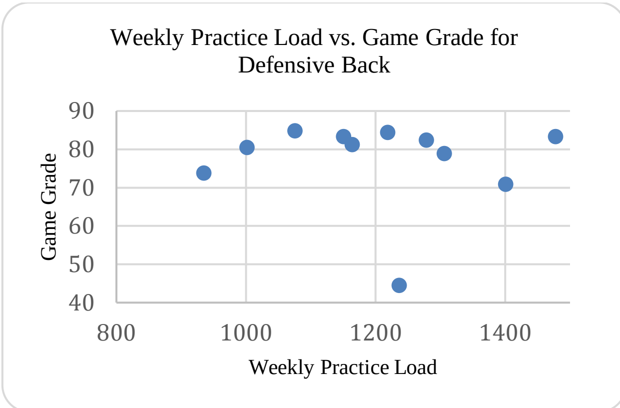

FIGURE III
SAMPLE RELATIONSHIP OF PRACTICE LOAD TO IN-GAME PERFORMANCE BY WEEK

Preliminary analysis shows there may be ideal practice loads, as the graph seems to take the expected form of a bell curve. While practice load is important to game performance, there are many other variables that can positively or negatively impact a player's performance. For future work, the Catapult data and Pro Football Focus data can be coupled with other data to be collected by the U.Va. Football program such as player sleep data, injury records, and travel schedules to build not only more comprehensive models to drive team and player success, but also to prevent injuries.

III. Analyzing Film Using Computer Vision

In both college and professional football, a critical component of preparing for an opponent is scouting. Scouting opponents commonly involves analyzing their game footage from earlier in the season. Currently, the U.Va. Football staff analyzes opponent footage by selecting that team's most relevant past games and tagging a number of descriptive fields for each play. These fields include play type, play formation, quarterback location, etc. Keeping a play-by-play record of these descriptive fields allows coaches to recognize patterns in their opponent's playstyle. However, manually assessing each frame of game footage and tagging these fields is time-consuming, which limits the number of games that can be tagged. This restricts the information available to U.Va. coaches when studying upcoming opponents. Not only can this task be time-intensive, but since it is done manually by different personnel, it can lack uniformity in input.

To address this limitation, an element of this project was dedicated to developing a proof of concept for automating film tagging using computer vision [6]. The method developed, "SCOUT-ID" is shown in Figure IV.

The Atlantic Coast Conference (ACC) regulates that film is to be prepared after each game in a structured way, with each team's offensive, defensive, and special teams plays to be sorted into their own respective MP4 files. Accompanying each MP4 file is an XML file that includes all attributes of the play that are tagged during games (and therefore provided to teams). These include down, distance, location on the field, and the frame at which a play starts. Therefore, by parsing these XML files, the beginning of each play can be scanned for and found in the respective MP4 file.

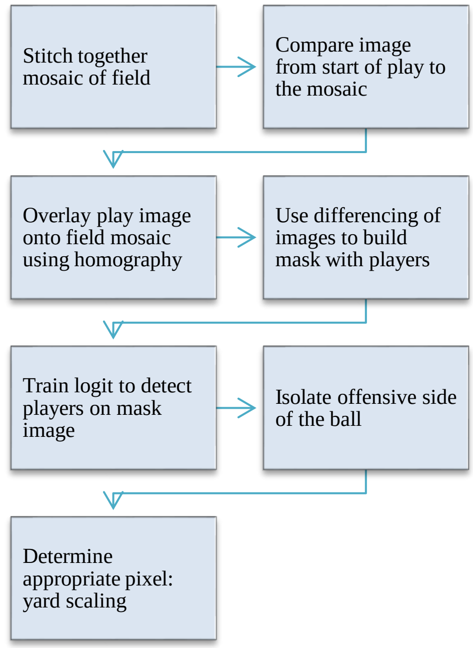

FIGURE IV
THE SIMPLIFIED SCOUT-ID PROCESS FOR USING COMPUTER VISION TO DETECT THE OFFENSE

The first step in the process is to create a mosaic of the football field for each game. Pictures from the game film are compared to extract matching key points using scale-invariant feature transform (SIFT) descriptors [7]. These match points are used to compute a 3x3 homography matrix which is used to perform a projective transformation on images so that images being compared share a common geometric plane. This is repeated for a series of images to fully capture the total area of the field into a single mosaic, as shown in Figure V. This can only be done with images captured from a shared viewing plane but at different angles, similar to constructing a panorama.

FIGURE V
PANORAMIC OF DUKE UNIVERSITY FOOTBALL FIELD DEVELOPED USING HOMOGRAPHY STITCHING

To accomplish this, kickoff plays within the special teams film were utilized, which by nature allow a full view of the football field within a single play. By isolating one in every 50 frames, enough images are gathered to complete a mosaic of the field. Throughout the process, each image is saved in a sparse array such that its pixels in a given column-row correspond to the same geometric coordinate in every other image. After creating this mosaic, the median value of the stacked images, excluding zero values, was determined for each pixel position. Based on the assumption that no pixel will be occupied by players more often than it is occupied by unobstructed field, taking the median value outputs the more frequently occurring pixel value of the field as opposed to the player. This generated a mosaic of the field that excluded players because coordinates that had 3 or more overlapping images typically only held a player at that location in one of the images, so the pixel value of the field was returned. This step is essential to the process, as a well-developed mosaic of the field allows for players in the foreground to be isolated from this background.

Once the mosaic is constructed, the offensive film of the opponent to be scouted can be analyzed. By parsing the XML document associated with this film MP4, the start of each play is known. This image frame indicating the start of a play is then retrieved from the MP4 file and compared to the mosaic of the field by layering it on top after transforming the background to intersect with the formation image. Once the background is warped to match the geometry of the formation image, the images can be directly compared, and players can be recognized as not appearing in the original mosaic, therefore a 'difference' in the images. The background of the formation image can then be subtracted and the pixel values of resulting image are thresholded to create a new image of the foreground only, (referred to as the mask) marking where each player is. The contours of this image are located to form bounding boxes around areas of interest, and features such as x,y coordinate, height, width, area, and a histogram of gradients (HoG) are recorded (shown in Figure VI). A logit model was then trained and used on these bounding boxes to filter out non-players from selection.

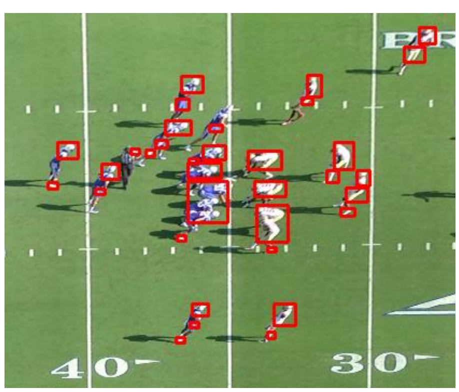

FIGURE VI
DETECTING POINTS OF INTEREST FROM DIFFERENCES

After players have been located, the offensive line was determined by searching for the highest concentration of pixels in the differenced image. The offensive side of the line of scrimmage was determined by finding the side which had the lowest concentration of pixels on either side of the line of scrimmage. Next, the relative distances must be calculated. Relative distances are found by using a probabilistic Hough transform, which can be used to find lines on the field. The probabilistic Hough transform was tailored to detect the hash marks and field lines, and then store these as lines in slope-intercept form. Since the hash marks and field lines are standardized throughout college football, these lines can then be compared to find a pixel: yard scaling. The line equations from the vertical field lines can then be used on the mask image which stores the player locations. By translating these lines across and calculating pixel values between them, the max of the sum of the vertical pixel values can locate the offensive line, shown in Figure VII. This offensive area is then to be cropped, and if not on the left of the image, flipped, so that formations between plays can be more easily compared.

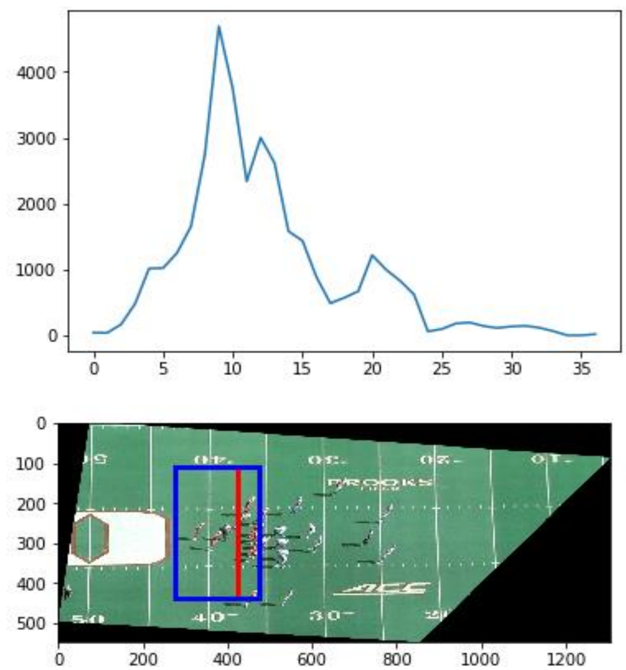

FIGURE VII
SUMMING PIXEL VALUES FROM DIFFERENCES ACROSS AN IMAGE TO DETECT AND ISOLATE OFFENSE

Through these steps, the offensive formation can now be classified by using a decision tree constructed by the team, which primarily relies on the locations of running backs, tight ends, and receivers.

CONCLUSION

Through the analysis of the fourth down decision tool, the development of player performance modeling, and the creation of a proof of concept methodology to automatically scout film, this research has supplemented tools from prior research and created new avenues to optimize performance. While building upon the prior work of previous researchers has proven effective, there are still more opportunities for data collection to supplement the existing tools and analyses, such as inputting tailored kicker and punter data into the fourth down decision model, collecting sleep or injury data to be added to the player performance model, and establishing infrastructure to scale an automated play formation classification tool. By providing recommendations to the U.Va. Football program to collect data in some of these areas of interest, a strong foundation has been built for future researchers to continue these efforts to integrate technology and data-driven solutions into the program.

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