Match Prediction and Analysis: Initial Report

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Introduction

This brief initial report presents a proprietary deep learning model (AI) designed to analyse past UFC bouts, that will be used to understand and predict athlete performance, as well as match outcomes.

Significant value and potential was found in this model, therefore few aspects of the model are addressed, and this report is intended to display its performance.

A vast database was collected and formed from various online resources. Features where engineered to obtain key performance metrics such as proportions, percentages, rates, and totals to quantify an athlete's damage, offence, defence, and physical advantages.
This data was used to train a deep learning model capable of predicting match outcomes with 71% accuracy, as well as outcome probabilities for Kelly risk mitigation and capitalising on positive expected value opportunities [11].

MMA is a sport with a lot of randomness, wherein there are athletes who may win when the odds are stacked against them. Paul Craig is a common example of this principle, submitting Ankalaev (6.5 decimal odds underdog) and injuring Jamahal Hill (3.25 decimal odds underdog). In some cases, dominant athletes in the eyes of the public constantly fall short of breaking through, such as Ankalaev who fails to top his weight class (draw and no contest with 3.85 and 4.1 decimal odds underdogs). In other instances, athletes who were once seen as invincible have been reduced to stepping stones for upcoming talents to build a name, such as Tony Ferguson, Jose Aldo and Henry Cejudo. Therefore, outliers who consistently reject the model, provide a source of motivation for further reports (are not covered in the scope of this report).

In addition to match outcome prediction, this technology can be used for athlete consulting. Jon Jones the consensus greatest fighter in history, accredits his success to his rigorous game plans. With this predictive technology it allows us to spot performance inconsistencies, and potentially even instances of foul play that harms the integrity of fair competition. When consulting athletes, data science can reveal secrets behind dominant victories, when dealing with mathematically unfavourable match ups. This can be done by projecting in-match statistics and assisting the game plan formation process, to produce better outcomes within the prediction technology. Currently, we are assisting one UFC fighter, as he prepares for his next match.

1 Dataset

The athlete's and event's features where collected from various API. The market odds data was collected over a period of 100 fights from Pinnacle [7], due to its high liquidity and smaller margins, which encourage volume based approaches, contrary to many popular bookies.
Modern bouts with the 5 minute rounds (3 or 5 rounds) and a 10 point must scoring system were modelled [1]. The practical implications of draws and no contests are statistically significant, however their inclusion in the modelling process provides difficulty. The models struggle to differentiate between matches with definitive winners and these outcomes (significantly reducing the accuracy of the model), due to the round performance inconsistencies [1] and overturned results (No Contest). Therefore, the model was trained on matches with winners. Table 1 illustrates this,

A hypothesis test was applied to investigate the binary nature of the outcomes with a significance level $\alpha = 0.05$ (for our dataset containing just matches with definitive winners).

- Null Hypothesis H_0: the probability of a blue corner victory is equal to the probability of a red corner victory.

Outcome	Frequency	Proportion
Red	4876	0.64
Blue	2662	0.35
Draw	48	0.0063
No Contest	74	0.0097
Total	7660	1.0

Table 1: Outcomes of UFC matches from the modern era. Red denotes a red corner victory, Blue denotes a blue corner victory, Draw denotes a draw between red and blue, and No Contest denotes a voided match outcome.

- Alternate Hypothesis H_1: the probability of a blue corner victory is different to the probability of a red corner victory.

The statistics of the test are shown in Table 2,

statistic	Value
P value	$8.6 \cdot 10^{-285}$
Z statistic	-36

Table 2: Statistics from the dataset containing just matches wih definitive winners

The high negative Z statistic is indicative of a large difference in the proportion of victories seen in both corners, and that the proportion of victories seen in the blue corner is significantly lower than the red corner. The P value is smaller than the significance level of 0.05, thus we reject the H_0. To conclude there is a distinct edge for athletes competing from the red corner.
This may harm the binary classification model as there will be a skew towards red corner athletes, decreasing the potential for identifying promising blue corner competitors (having a high number of false positive cases). There are various papers that discuss the psychological implications and crowd dynamics associated with wearing red in competition [2, 3, 6]. To conclude, threshold values, calibrators and oversampling (of the less populated class) where applied to binary classifier architectures [8], to address this skew.

2 Model and Method

Many models, with different features, were stacked and bagged. One model used in the cohort, was a Swish-based deep neural network, with dropout, which was trained with a binary cross entropy loss function and the Adam optimiser (with L2 regularisation). Each forward pass can produce slightly different outcomes, due to the dropout adding variance in the network architecture [5]. Consequently, the outputs (when averaged) can be visualized as an average over many match simulations, which helps reduce the risk of overfitting.
Dropout randomly "turns off" a fraction of the units during training, the network essentially samples through a range of subset architectures, which introduces stochasticity and uncertainty in the network parameters. This stochastic behaviour allows the model to form a distribution over possible functions, analogous to Bayesian models which incorporate network parameters as distributions [10]. Thus, the architecture exhibits Bayesian-like properties and inherent regularisation characteristics, making it advantageous for sports betting applications that require robust and generalizable models [4].
Other architectures were used and combined with a meta layer [9].
The dataset, which contains all historic match data, was cleaned and feature engineered. Only matches with a definitive winner were modelled, therefore this can be viewed as a binary classification problem (addressed in Section 1). The dataset was split into a test set (last 100 matches), a training and validation set.

3 Betting

Several bankroll strategies where investigated to find the optimal betting strategy over the last 100 fights using our model. Two simple and commonly used strategies include,

- The Kelly criterion is used to mitigate long term betting risks, by providing optimal bankrolls given the expected value and odds [11]. Most UFC bookies only allow betters to place odds before the event starts, so a fractional Kelly was adopted to maximise our profits across the event. This method only includes positive expected value (EV) and positive Kelly opportunities. The kelly method can adjusted aggressively or conservatively, by using a higher (aggressive) or lower (conservative) proportion of the Kelly fraction.
- We can also bet a fixed amount (or percentage) on each match on the athlete that the model has predicted to win.

There are various modifications for these two basic bankroll strategies, such as underdog betting (higher payout and large EV) or UFC veteran betting.

4 Results

Figure 1 shows pot growth over the last quarter (last 100 UFC bouts) - using the model and applying the betting strategies discussed in Section 3.

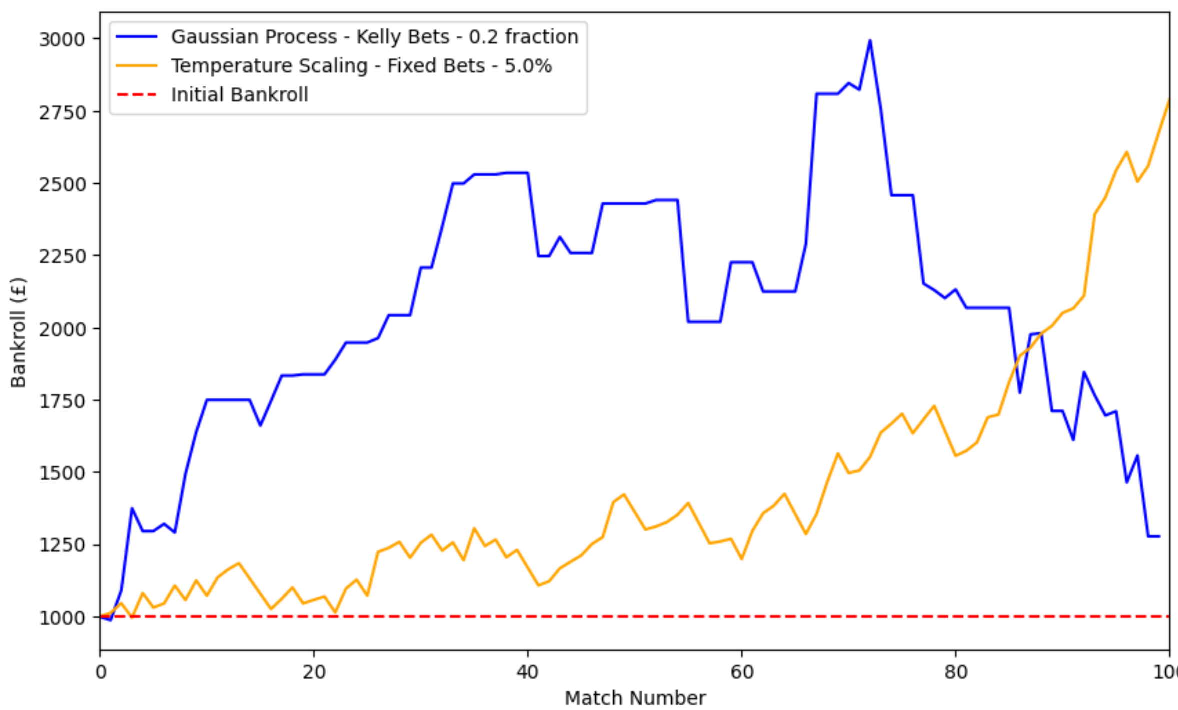

Figure 1: Wealth growth over the last 100 UFC matches using different betting strategies.

The profit of the best strategy (model prediction fixed percentage 5%) was 179% quarterly (100 fights happen over a 3 month period). Extrapolating the performance over the last 100 fights gives 6000% profit annually.

$$(2.79^4 - 1) \cdot 100\% = (60.592... - 1) \cdot 100\% \approx 6000\% \tag{1}$$

The *years* it takes to reach a certain pot I_g from an initial pot I_0 with this crude projection is,

$$years = \log_{60} \frac{I_g}{I_0} \tag{2}$$

For the Kelly betting strategy (Gaussian process calibrated output), the quarterly profit was 27%. Both elementary methods, show promise for further betting activities. An experiment with a randomly sampled test set it needed to confirm the findings of this report.

5 Conclusion

The findings of the report are theoretical and lack error analysis, leaving much room for skepticism. Athlete performance's vary and a risk score needs to be associated for each fighter to find the variance of their performances.
The model, bankroll strategies and market analysis are constantly improving. There are ample opportunities for variants of the model across a spectrum of sports, and it has clearly shown promise for this current application. The next stage of this project will include developing additional analytical technologies for fighters and experimenting with new models and features. The Kelly criterion was out performed by the fixed percentage and fixed amount bankroll strategies. Thus, a larger test set will be experimented on to test the validity of treating the current calibrated outputs as probabilities, and finding the optimum betting strategy.

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6 Betting odds

Table 3: Decimal betting odds from the last 100 UFC fights, collected from Pinnacle

Fighter 1	Fighter 2	Odds 1	Odds 2
Sean O'Malley	Merab Dvalishvili	1.71	2.1
Alexa Grasso	Valentina Shevchenko	1.74	2.14
Brian Ortega	Diego Lopes	2.46	1.53

Fighter 1	Fighter 2	Odds 1	Odds 2
Daniel Zellhuber	Esteban Ribovics	1.44	2.84
Ronaldo Rodriguez	Ode Osbourne	1.62	2.36
Irene Aldana	Norma Dumont	1.91	1.91
Manuel Torres	Ignacio Bahamondes	2.3	1.57
Yazmin Jauregui	Ketlen Souza	1.25	3.75
Edgar Chairez	Joshua Van	2.8	1.43
Raul Rosas Jr.	Aoriqileng	1.15	5.8
Gilbert Burns	Sean Brady	2.6	1.52
Jessica Andrade	Natalia Silva	3.5	1.31
Steve Garcia	Kyle Nelson	1.56	2.55
Matt Schnell	Cody Durden	3.4	1.33
Trevor Peek	Yanal Ashmouz	1.8	2.05
Rongzhu	Chris Padilla	1.57	2.3
Isaac Dulgarian	Brendon Marotte	1.11	7.0
Felipe dos Santos	Andre Lima	1.83	2.0
Yizha	Gabriel Santos	3.4	1.34
Jaqueline Amorim	Vanessa Demopoulos	1.2	4.8
Andre Petroski	Dylan Budka	1.4	3.05
Zygimantas Ramaska	Nathan Fletcher	2.1	1.72
Jared Cannonier	Caio Borralho	2.22	1.69
Angela Hill	Tabatha Ricci	2.2	1.71
Robert Valentin	Ryan Loder	1.71	2.15
Kaan Ofli	Mairon Santos	2.64	1.51
Neil Magny	Michael Morales	2.8	1.46
Edmen Shahbazyan	Gerald Meerschaert	1.68	2.24
Dennis Buzukja	Francis Marshall	2.14	1.69
Zachary Reese	Jose Daniel Medina	1.13	6.5
Viacheslav Borshchev	James Llontop	1.51	2.64
Jacqueline Cavalcanti	Josiane Nunes	2.45	1.57
Wang Cong	Victoria Leonardo	2.64	1.51
Dricus Du Plessis	Israel Adesanya	2.0	1.83
Kai Kara-France	Steve Erceg	2.72	1.49
Mateusz Gamrot	Dan Hooker	1.3	3.5
Tai Tuivasa	Jairzinho Rozenstruik	2.32	1.59
Li Jingliang	Carlos Prates	2.0	1.38
Junior Tafa	Valter Walker	1.95	1.87
Josh Culibao	Ricardo Ramos	1.6	2.4
Casey O'Neill	Luana Santos	2.28	1.63
Jack Jenkins	Herbert Burns	1.13	6.5
Tom Nolan	Alex Reyes	1.09	9.5
Song Kenan	Ricky Glenn	1.48	2.75
Stewart Nicoll	Jesus Aguilar	1.48	2.76
Marcin Tybura	Serghei Spivac	2.3	1.67
Damon Jackson	Chepe Mariscal	2.85	1.42
Danny Barlow	Nikolay Veretennikov	1.25	4.5
Chris Gutierrez	Quang Le	1.17	6.0
Yana Santos	Chelsea Chandler	1.95	1.87
Toshiomi Kazama	Charalampos Grigoriou	2.8	1.46
Karol Rosa	Pannie Kianzad	1.44	3.2
Jhonata Diniz	Karl Williams	3.0	1.41
Youssef Zalal	Jarno Errens	1.39	3.1
Stephanie Luciano	Talita Alencar	1.65	2.3
Cory Sandhagen	Umar Nurmagomedov	4.33	1.36
Shara Magomedov	Michal Oleksiejczuk	1.37	3.05
Marlon Vera	Deiveson Figueiredo	2.25	1.73
Tony Ferguson	Michael Chiesa	5.1	1.23
Mackenzie Dern	Loopy Godinez	1.79	2.2

Fighter 1	Fighter 2	Odds 1	Odds 2
Joel Alvarez	Elves Brener	1.66	2.32
Azamat Murzakanov	Alonzo Menifield	1.42	3.5
Mohammad Yahya	Kaue Fernandes	4.0	1.28
Shamil Gaziev	Don'Tale Mayes	1.36	3.5
Guram Kutateladze	Jordan Vucenic	1.51	2.9
Viktoriia Dudakova	Sam Hughes	1.57	2.8
Jai Herbert	Rolando Bedoya	1.91	2.04
Sedriques Dumas	Denis Tiuliulin	1.46	2.8
Leon Edwards	Belal Muhammad	1.47	2.75
Tom Aspinall	Curtis Blaydes	1.51	2.64
King Green	Paddy Pimblett	1.88	1.94
Christian Leroy Duncan	Gregory Rodrigues	1.8	1.95
Arnold Allen	Giga Chikadze	1.38	3.4
Nathaniel Wood	Daniel Pineda	1.25	4.6
Molly McCann	Bruna Brasil	1.29	3.75
Jake Hadley	Caolan Loughran	2.5	1.54
Muhammad Mokaev	Manel Kape	1.56	2.4
Oban Elliott	Preston Parsons	2.5	1.63
Modestas Bukauskas	Marcin Prachnio	1.67	2.1
Sam Patterson	Kiefer Crosbie	1.21	5.0
Mick Parkin	Lukasz Brzeski	1.22	5.25
Shauna Bannon	Alice Ardelean	1.43	2.8
Amanda Lemos	Virna Jandiroba	2.15	1.74
Steve Garcia	SeungWoo Choi	1.67	2.2
Kurt Holobaugh	Kaynan Kruschewsky	2.25	1.74
Dooho Choi	Bill Algeo	2.9	1.53
JeongYeong Lee	Hyder Amil	1.53	2.85
Brian Kelleher	Cody Gibson	2.75	1.4
Miranda Maverick	Dione Barbosa	1.53	2.75
Loik Radzhabov	Trey Ogden	1.81	2.2
Luana Carolina	Lucie Pudilova	2.05	1.72
Mohammed Usman	Thomas Petersen	1.68	2.28
Rose Namajunas	Tracy Cortez	1.5	2.7
Santiago Ponzinibbio	Muslim Salikhov	1.68	2.24
Gabriel Bonfim	Ange Loosa	1.28	4.2
Julian Erosa	Christian Rodriguez	2.42	1.59
Joshua Van	Charles Johnson	1.58	2.7
Jasmine Jasudavicius	Fatima Kline	1.83	1.91
Montel Jackson	Da'Mon Blackshear	1.67	2.2
Luana Santos	Mariya Agapova	1.25	4.1