Formula-1 Race Winner Predictor

A Project Report Submitted

to

MANIPAL ACADEMY OF HIGHER EDUCATION

For Partial Fulfillment of the Requirement for the

Award of the Degree

Of

Bachelor of Technology

in

Information Technology

by

Abhijeet Gupta, Abhishek Agarwal, , Ria Sharma

210911030, 210911044, 210911058

Under the guidance of

Dr. Swathi B.P
Assistant Professor
Department of I&CT
Manipal Institute of Technology
Manipal, Karnataka, India

Dr. Kaliraj S
Assistant Professor
Department of I&CT
Manipal Institute of Technology
Manipal, Karnataka, India

MANIPAL INSTITUTE OF TECHNOLOGY
MANIPAL
A Constituent Unit of MAHE, Manipal

April 2024

ABSTRACT

Formula 1 Racing stands as a pinnacle of technological advancement in the sporting world, continually pushing boundaries with mid-season developments and strategic intricacies. However, despite meticulous planning and cutting-edge technology, uncertainties persist, manifesting in unexpected crashes, strategic twists, and dynamic race outcomes. This project endeavors to harness the power of machine learning, specifically logistic regression, to predict Formula 1 race winners. Leveraging data sourced from the Ergast API spanning Formula 1's history, the project embarks on a journey of data preprocessing, exploratory data analysis, feature engineering, and model building. The Logistic Regression algorithm, alongside Support Vector Machines (SVM) and Neural Network Classifiers, serves as the primary tool for prediction. Through a classification approach, the model aims to anticipate the drivers most likely to claim victory in each race, offering insights with implications spanning sports betting, team performance analysis, media coverage, fan engagement, and marketing strategies. By unraveling the enigma of Formula 1 predictability, this project contributes to a deeper understanding of the sport's dynamics and technological evolution.

Sustainable Development Goal (SDG) 9: Industry, Innovation, and Infrastructure

This project aligns with SDG 9, which aims to build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation. By leveraging machine learning techniques to predict Formula 1 race winners, the project embodies innovation in sports analytics. Furthermore, it contributes to the optimization of performance strategies for Formula 1 teams, promoting technological advancements within the racing industry. Additionally, by enhancing fan engagement and media coverage, the project fosters inclusivity and awareness within the realm of motorsports. Overall, the project's objectives resonate with SDG 9 by driving advancements in technology and infrastructure within the context of the Formula 1 ecosystem.

INTRODUCTION

Formula One, affectionately known as F1, stands as a beacon of motorsport excellence, captivating audiences worldwide with its blend of speed, skill, and spectacle. Boasting a roster of the planet's finest racing talent, F1 delivers an adrenaline-fueled saga of competition across a calendar brimming with prestigious races. With a global audience spanning diverse backgrounds, F1's allure transcends boundaries, drawing millions into its orbit of excitement.

Rooted in the early 20th century, Formula One's journey crystallized in 1946 with the creation of the Formula One World Championship by the Fédération Internationale de l'Automobile (FIA). This pinnacle of motorsport encompasses a series of illustrious Grand Prix races held on circuits worldwide. Each race sees formidable teams, each with a duo of drivers, navigate meticulously crafted tracks. From sweeping straights to treacherous twists, these circuits challenge the limits of both man and machine.

At the heart of Formula One lies its technological marvels – the racing cars. Crafted with precision engineering, these aerodynamic marvels boast staggering speeds, propelled by engines capable of generating over 900 horsepower. Constructed from lightweight materials such as carbon fiber, these masterpieces accelerate from 0 to 60 mph in a mere heartbeat, hurtling towards top speeds exceeding 200 mph.

Behind every roaring engine lies a powerhouse of innovation and expertise – the teams. With budgets soaring into the millions, each team commands a legion of top-tier engineers, designers, and mechanics. Together, they sculpt and refine their racing chariots, pushing the boundaries of performance and safety.

And then there are the drivers – the gladiators of the modern era. Revered for their unparalleled skill and unwavering resolve, these athletes embody the pinnacle of human achievement. Endowed with lightning-fast reflexes and an indomitable spirit, they brave extreme G-forces and high-pressure showdowns, etching their names in the annals of sporting history.

Yet, beyond the roar of engines and the thrill of speed, Formula One transcends mere sport. It is a global phenomenon, a tapestry woven with passion and fervor. From packed grandstands to living rooms ablaze with excitement, F1's resonance echoes across continents, uniting fans in a shared love for the extraordinary.

In conclusion, Formula One is not merely a sport – it is an ode to human ingenuity, perseverance, and passion. As it continues to push the boundaries of technology and engineering, Formula One remains a timeless testament to the indomitable human spirit. So, whether you're a fervent devotee or a casual admirer, the world of Formula One beckons, promising an exhilarating journey like no other.

LITERATURE SURVEY

Here we have referred some state-of-the-art papers in this domain.

A paper [l] from a book about trends in Machine Learning looks at cost-effective alternative options for Formula 1 racing teams. They performed some research on the current methods of data collection, analysis and prediction. It was discovered that a big portion of the league's racing firms require a cheap, effective, and automated data interpretation method. The need for powerful prediction software grows, just as the modern trend behind F1 increases.

The research of Leon Sobrie [2] shows use of tree-based models in similar predictions. Their paper shows 3 different analysis, the first focuses on top 3 finishers and high performances in F1 races. The second analysis focuses on actual completion of the race, further helping make the races safer and minimize human and technical errors. The final analysis comprises the qualifying ability for the race to make sure the teams have 2 drivers at the start

Another paper[3] talks about making predictions in F1 or motor racing by using Artificial Neural Network(ANN). It is divided into two parts, the first part explains what an ANN is and gives an in-depth study of its many features, functions and layers. The second part focuses more on the implementation and methodologies such as data collection, comparison and much more. Some points in paper also talk about minimizing errors by regularization.

Speaking of regularization in Machine learning techniques, a research paper[4] in 2018 also goes in depth about the various methods of regularization. Not every method or technique is going to work in every situation, hence specific methods need to be applied for specific models. The model the paper primarily focused on was ANN. It used libraries from Tensorflow, and performed an analytical comparison between each algorithm and method.

Getting back to Formula 1, an interesting research paper] 5] shows the significant importance of pit stops. It focuses less on predicting results and more on strategizing the use of these pit stops. In their paper they have presented their own Virtual Strategy Engineer (VSE) and described how it improves on the pre-existing methods like solving quadratic optimization problems or studying race simulations. Finally they have provided an ‘example race’ to show their VSE.

Since our project is using SVMs we have referred some papers which purely focus on use and features of SVM. A survey [6] teaches us about the use of SVMs in learning, classification, regression and forecasting. They have summarized almost everything there is to know about SVMs and even talked about the various parameters and how to optimize them. They have also provided information about new types of SVM, like FSVM and TSVM. Their primary focus is in the area of mobile multimedia. In the end, the paper discusses more about the future direction of SVM and its improvements.

We also looked at papers with previously mentioned FSVM[7] and TSVM[8]. These papers provide detailed explanation on their respective subjects. SVMs have been used in many other prediction models such as predicting quality of soil[9], predicting diseases like diabetes in patients[10], school student performances[11] and even early detection of Covid-19 in patients[12]. We also looked at papers more focused on using SVM in predicting races like horse raees[13].

Further exploration of SVM and its many uses, as well as comparisons with other models were studied in this paper [14]. The paper mentions how SVMs have more advantages than other algorithms in cases such as analyzing problems theoretically using concepts from computational learning theory.

Finally, we needed to look at the specific parameters for our SVM. There are 4 parameters that are typically used: Linear, polynomial, RBF and sigmoid. A research paper [15] published by IEEE gives us proper insight on how each parameter and kernel works and how they are tuned for optimal results. It also goes in-depth about the multiple uses of SVM in our current technological age.

OBJECTIVES

Data Preprocessing:

1. **Data Collection**:
   - The data will be collected from Ergast API, which holds data harvested from the Formula 1 website. The API itself holds all information on races, results, drivers, qualifying, lap times, pit stops, constructors' and drivers' standings and circuits from Formula 1's inception in 1950 to date.
2. **Data Cleaning and Preprocessing**:
   - Data cleaning involves handling missing values, removing outliers, and addressing inconsistencies or errors in the dataset.
   - This might involve imputing missing values, scaling the features, and removing outliers for numerical variables.
   - This might involve encoding categorical variables into numerical format (e.g., one-hot encoding).

Data Mining Steps:

1. **Exploratory Data Analysis (EDA)**:
   - Visualise the data using appropriate techniques, such as histograms for numerical variables and bar plots or pie charts for categorical variables.
   - Understand the distribution of each variable, identify patterns, and explore relationships between variables.
2. **Feature Engineering**:
   - This involves creating new features, transforming existing features, or selecting relevant features to improve the model's predictive performance.
   - Techniques may include feature scaling, dimensionality reduction, or creating interaction terms.
3. **Model Building**:
   - Select an appropriate machine learning algorithm based on the problem type and data characteristics.
   - Train the model on a portion of the dataset (training set) and evaluate its performance on a separate portion (validation or test set).
4. **Model Evaluation and Optimization**:
   - Evaluate the model's performance using appropriate evaluation metrics such as accuracy, precision, recall, F1-score, etc.
   - Perform hyperparameter tuning to optimise the model's performance further.
   - Use techniques such as cross-validation to ensure the model's generalisation ability.

METHODOLOGY

To predict the likelihood of a certain driver winning a Grand Prix and compare it to the bookmakers' odds. This projectwill be split into three parts:

- Data collection
- Data analysis
- ML Modelling

Data Collection:

Datasets:

- **Races:** this data frame contains information about all the championships and races from 1950 to 2019,including their location and link to Wikipedia page.
- **Results:** for second data frame, iteration was done through each year and each round of races file to querythe Ergast API and get information about all the drivers' results. It includes features such as grid and finishing position of each driver, their teams, and other less relevant variables such as date of birth, nationality and finishing status, which will be explored later to check whether there could be a correlation between the age of the drivers and their performance, if racing in their home country could have any psychological impact, or if some drivers are more prone to crash than others.
- **Driver Standings:** Points are awarded during the Championship based on where drivers and teams finishthe race. Only the first 10 drivers finishing are awarded points, with the winner receiving 25 points. The Ergast API provides the number of points, wins and the standing position of each driver and team throughout the Championship. Because the points are awarded after the race, a lookup function to shiftthe points from previous races within the same Championship had to be created.
- **Constructor Standings:** The Constructors Championship was awarded for the first time in 1958 so there isno data prior to that year. The data mining process is the same as the driver standings', eventually applying the same lookup function to get the data before the race.
- **Qualifying:** Since 2006, qualifying takes place on a Saturday afternoon in a three-stage "knockout"
  system where the cars try to set their fastest lap time. In the past, qualifying would only consist of one ortwo sessions, causing missing data in my data frame. Only the best qualifying time for each driver was considered, regardless of how many qualifying sessions were held in that year. The best qualifying time isreflected in the grid position, hence calculation of the cumulative difference in times between the first qualified car and the others, hoping that it might give me an indication of how much faster a car is compared to the other ones will be done later.
- **Weather:** Weather in Formula 1 plays a significant role on the choice of tires, on the drivers'
  performance and on the overall teams' strategy. Wikipedia links of each race appended in the races_df and scrape the weather forecast were iterated. Since the

Wikipedia pages do not have a consistent htmlstructure, further investigation was done with a few different tables, and even at that point there were many missing values. However, it was noticed that the remaining information in the corresponding pages were in a different language. Selenium was used to click on the Italian page for each link and append the
missing weather data. Eventually, a dictionary was created to categorize the weather forecasts and mapthe results.

All the above datasets were collected from the Ergast F1[26] data repository.

Data Analysis:

The first drivers’ world championship was held in 1950 at the British Grand Prix at Silverstone and comprisedonly seven races. The number of Grand Prix per season varied over the years, averaging 19 races in the latestseasons. The location of the races has also varied over time, depending on the suitability of the track and
other financial reasons. Currently, only the Italian and British Grand Prix are the only events that didn’t miss aseason since 1950.

How important is the pole position?

During qualification sessions the drivers try to set their fastest time around the track and the grid position isdetermined by the drivers’ best single lap, with the fastest on pole position. Starting on pole position is crucial in those circuits where overtaking is more difficult, in addition to having the advantage of staring afew meters ahead and on the normal racing line, which is usually cleaner and has more grip. The followinggraph shows the correlation between staring in pole position and winning the race in some of the most popular circuits.

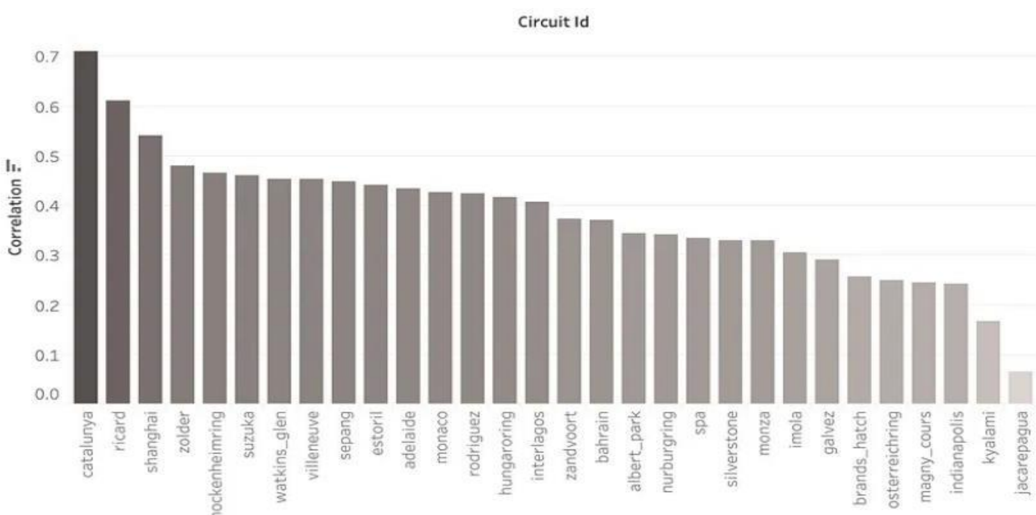

Figure 1. P1 — Q1 correlation

What’s the impact of racing in your home country?

The advantage of racing in your home country could be attributed to the psychological impact that supporting fans have on the drivers, as well as driving near home in familiar situations. The bar chart showssome of the nationalities of the drivers that ended up first on the podium during the years and their respective percentage count of wins over all circuit’s races. Despite not showing a sharp difference, we cannotice that even psychological factors play a role in the likelihood of winning a race.

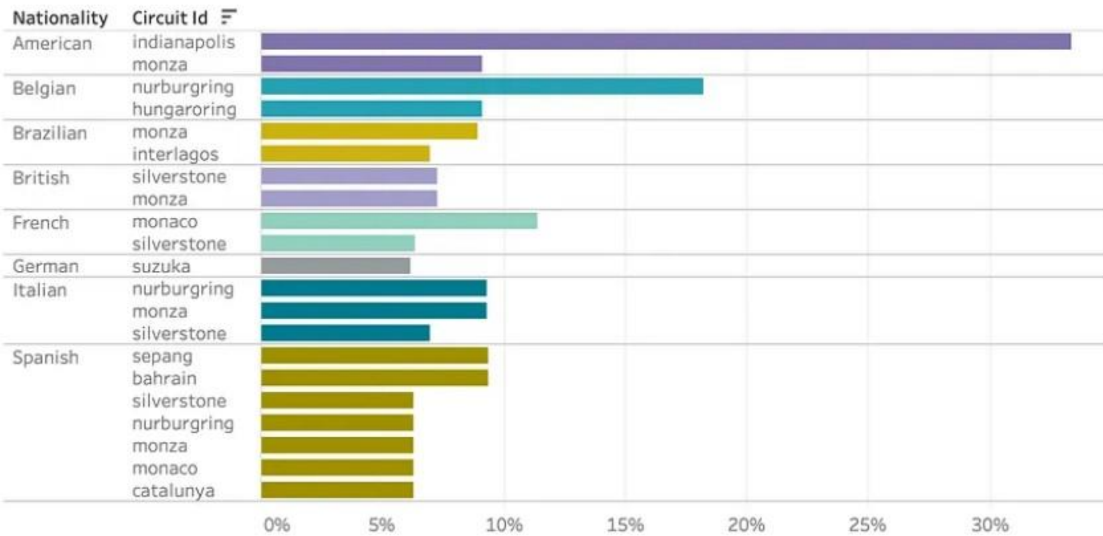

Figure 2. Winners by nationality

Most dangerous circuits

Some of the circuit layouts have been redesigned over the years to meet stricter safety requirements.

Currently, most of the circuits are specifically constructed for competitions, to avoid long and fast straights ordangerous turns. However, some races are still held at street circuits, such as the Monaco Grand Prix, which is still in use mainly for its fame and history, despite not conforming with the latest strict measures. Thefollowing tree-map shows some of the most popular tracks by number of incidents or collisions.

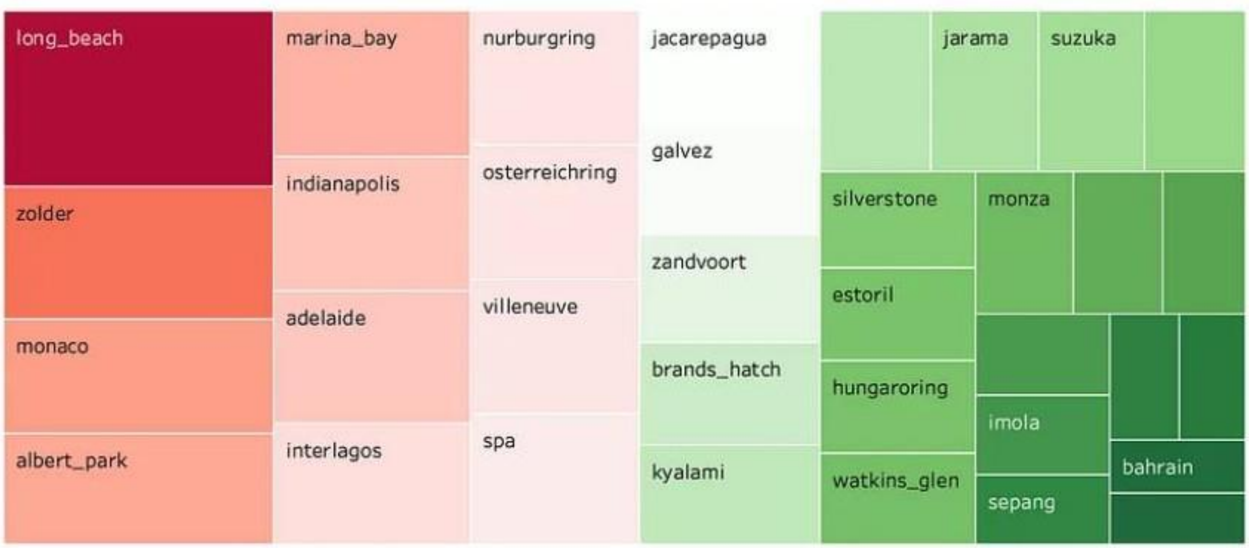

Figure 3. Most dangerous circuits by incidents

Which teams had more car failures?

The bar chart shows which teams that raced in the last few seasons experienced the highest number of carproblems over the years, including engine failures, brakes, suspension, or transmission problems.

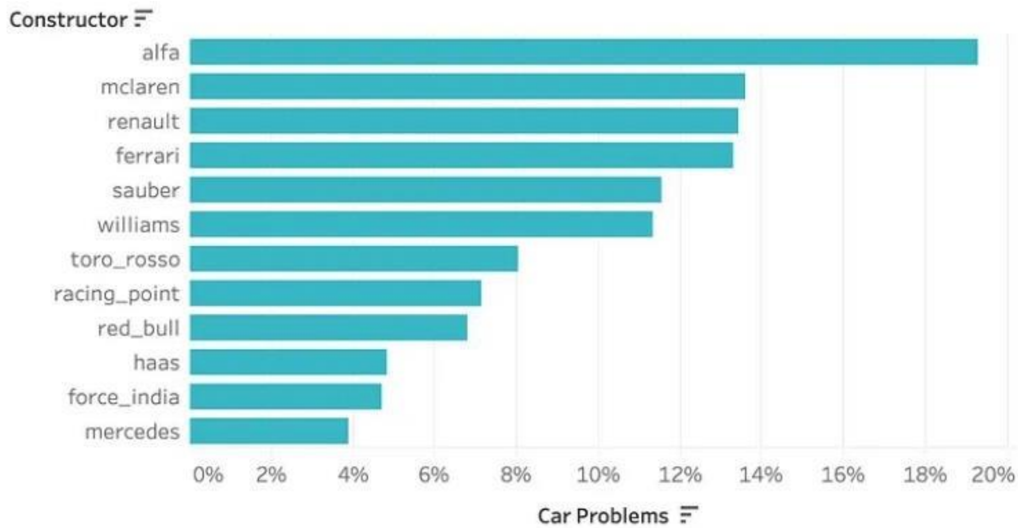

Figure 4. Car problems ratio witnessed by teams.

Who's more prone to crash?

Cars in Formula 1 can reach top speeds of 375 km/h (233 mph) so crashes can ultimately terminate the racefor the drivers. The chart below shows the ratio of crashes of some of the drivers that raced in the last two seasons.

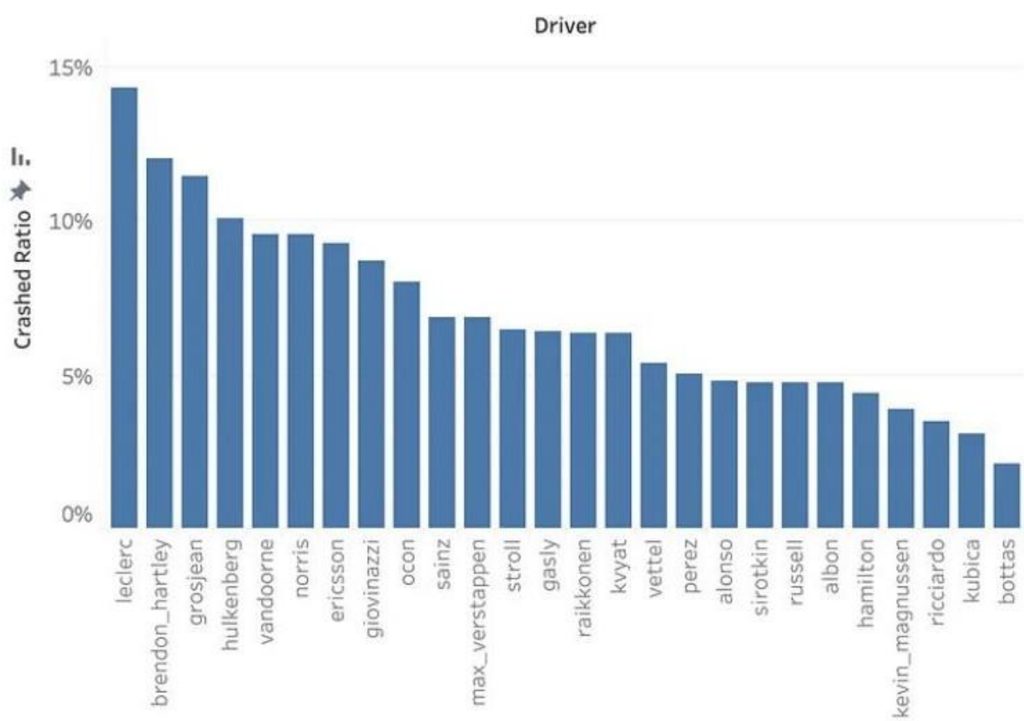

Figure 5. Crash ratio by 2018–2019 driver

How does age affect the championship positions?

In the early years of the world championship, most leading drivers were in their forties: Nino Farina won thefirst world title when he was 43 and Luigi Fagioli set the record of being the oldest winner in F1 history in 1952, aged 53 and unlikely to be ever surpassed in the years to come. However, it was only a matter of time before they got replaced by the new generation. From the 1960s to 1993 the average age was around 32 years old and in the latest seasons there are only a few drivers aged over 30. The following scatterplot shows the age of the winning drivers from the first inaugural season, showing a downward sloping trend line.

Figure 6. Winning drivers' age

IMPLEMENTATION DETAILS

ML Modelling:

This last section will address the following topics: the metrics that were used to evaluate the best model, theprocess of merging data and eventually Machine Learning modelling with neural networks.

Success metrics:

- Precision score — percentage of correctly predicted winners in 2019 season.

Merging Data:

Six different data frames were merged using common keys. The final data frame includes information of races,results, weather, driver and team standings and qualifying times from 1983 to 2019.

The age of drivers was calculated and the cumulative difference in qualifying times to have an indicator ofhow much faster the first car on the grid is compared to the other ones for each race.

Machine Learning Modelling:

To predict the first place on the podium for each race in 2019, the target variable can be treated as a **classification.**

In a **classification problem** the target is mapped 0 and 1 (winner) prior to modelling so, there might be morethan one winner or no winner at all depending on the predicted probabilities. Because the algorithm is not smart enough to understand that only one winner is needed for each race, hence a different scoring functionfor classification that ranks the probabilities of being the winner of the race for each driver. The probabilities are sorted from highest to lowest and the driver with the highest probability is mapped as the winner of the race.

Algorithms Used:

- **Logistic Regression:** It is a classification technique borrowed by machine learning from the field of statistics. Logistic Regression is a statistical method for analyzing a dataset in which there are one ormore independent variables that determine an outcome. The intention behind using logistic regression is to find the best fitting model to describe the relationship between the dependent and the independent variable.

- **SVM Classifier (Support Vector Machines):** It is a supervised machine learning algorithm used for both classification and regression. Though we say regression problems as well it's best suited for classification. The objective of the SVM algorithm is to find a hyperplane in an N-dimensional space that distinctly classifies the data points. The dimension of the hyperplane depends upon the numberof features. If the number of input features is two, then the hyperplane is just a line. If the number of input features is three, then the hyperplane becomes a 2-D plane. It becomes difficult to imagine when the number of features exceeds three.

- **Neural Network Classifier:** A neural network consists of units (neurons), arranged in layers, which convert an input vector into some output. Each unit takes an input, applies a (often nonlinear) function to it and then passes the output on to the next layer. Generally, the networks are defined to be feed-forward: a unit feeds its output to all the units on the next layer, but there is no feedbackto the previous layer. Weightings are applied to the signals passing from one unit to another, and it is these weightings which are tuned in the training phase to adapt a neural network to the problem at hand. This is the learning phase. Neural networks have found application in a wide variety of problems. These range from function representation to pattern recognition.

RESULTS

driver	podium	proba_0	proba_1	actual	predicted
max_verstappen	1	0.651345	0.348655	1	1
hamilton	5	0.696430	0.303570	0	0
bottas	3	0.834249	0.165751	0	0
leclerc	2	0.879126	0.120874	0	0

Figure 7. Screenshot of result

The dataset contains parameters (P1-Q1 correlation, nationality, driver age, crash ratio, car failures, most dangerous circuit) that we are using to calculate the probability of the driver winning which are tested against the actual podium data.
proba_0 is the probability of a driver not winning the race and **proba_1** is the probability of driver winning the race which is calculated using the function predict_proba of the scikit library.
We are passing the parameters in 3 different ML models that are Neural Network Classification, Support Vector Machines and Logistic Regression. Later, the predict_proba function is applied on the results obtained from ML model which calculates the probability of winning and not winning. The final result is sorted according to the proba_1 column values in descending order. The driver with highest probability is the winner according to the model which is assigned a value 1. It is then tested against the actual podium position. If the predicted value is equal to the actual value, the model has successfully predicted the correct winner.
In this case, even if Max Verstappen only has a probability of 0.35 of winning, because it's the highest probability of winning in that race, the function (Neural Network Classifier) correctly maps him as the winner.

Findings:

After taking a few days to run all the grid searches, classification with neural networks seem to return the highest scores, correctly predicting the winner for 62% of the races in 2019, which corresponds to 13/21 races.

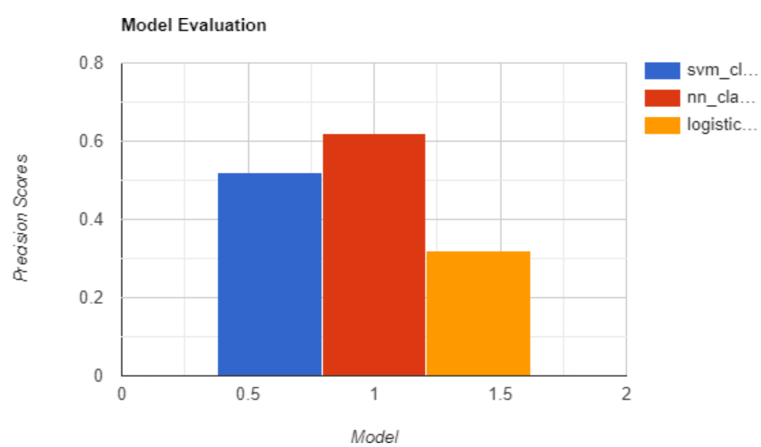

Figure 8. Model comparison

CONCLUSION

Neural Networks returned a score higher than SVM classifier in previous years, hence NN classifierwould be the perfect algorithm to predict.
Considering feature importance according to linear regression, the grid position seems to play the most important role in predicting the winner, along with other features such as teams or points priorto the race.
The hardest circuits to predict turned out to be Albert Park, Baku, Spa, Monza, and Hockenheim Ringprobably because more accidents or overtaking take place.
For future research on this area, the limitations of the project point towards fine-tuning algorithms using exhaustive search at the expense of time complexity. Predicted rankings for each race have room for improvement and better optimization of the algorithms. Another suggestion would be to look into Deep Learning solutions for neural networks as they have been used in mostly all of the literature reviewed and could provide new insights on top of the already chosen models. In addition, selection of additional feature such as individual lap-times, racing incidents or pit stops can play the role of a source of data enrichment as well as deploying specialized tools for dimensionality reduction and feature selection. As outlined in the results and discussion section, models have failed to account the relationship between the driver and the corresponding constructor team. A solution to investigate for this issue can be solved by additional constructor data collection. To conclude, the proposed framework has proven to predict championship standings of the current F1 season to a considerable degree. Further work as suggested in the paragraph above as well as evaluation of novel models can result into even more robust predictions. As suggested, more granular data about driver performance in terms of lap times for a specific racing event but also about constructor performance can be introduced to support this statement. Collaborative efforts have already converged at a larger scale towards F1 predictive analytics, with data being analyzed and modeled from multiple sources, not only historical data that this project encompasses, but also engineering data from factories and telemetry data from car performance indicators.

REFERENCES

- Bühlmann, P., & Yu, B. (2003). Boosting with the l 2 loss: regression and classification. Journal of the American Statistical Association, 98(462), 324–339.
- Bunker, R. P., & Thabtah, F. (2019). A machine learning framework for sport result prediction. Applied computing and informatics, 15(1), 27–33.
- Drucker, H. (1997). Improving regressors using boosting techniques. In Icml (Vol. 97, pp. 107–115).
- Edelman, D. (2007). Adapting support vector machine methods for horser ace odds prediction. Annals of Operations Research, 151(1), 325–336.
- Friedman, J. H. (2017). The elements of statistical learning: Data mining, inference, and prediction. springer open.
- Gu, W., Foster, K., Shang, J., & Wei, L. (2019). A game-predicting expert system using big data and machine learning. Expert Systems with Applications, 130, 293–305.
- Haghighat, M., Rastegari, H., Nourafza, N., Branch, N., & Esfahan, I. (2013). A review of data mining techniques for result prediction in sports. Advances in Computer Science: an International Journal, 2(5), 7–12.
- Horvat, T., & Job, J. (2020). The use of machine learning in sport outcome prediction: A review. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10(5), e1380.
- Jenkins, M., & Floyd, S. (2001). Trajectories in the evolution of technology: A multi-level study of competition in formula 1 racing. Organization studies, 22(6), 945–969.
- Lessmann, S., Sung, M.-C., & Johnson, J. E. (2009). Identifying winners of competitive events: A svm-based classification model for horserace prediction. European Journal of Operational Research, 196(2), 569–577.
- Liu, Y., Wang, Y., & Zhang, J. (2012). New machine learning algorithm: Random forest. In International conference on information computing and applications (pp. 246–252).
- Moore, A. W., & Lee, M. S. (1994). Efficient algorithms for minimizing cross validation error. In Machine learning proceedings 1994 (pp. 190–198). Elsevier.
- Ofoghi, B., Zeleznikow, J., MacMahon, C., & Dwyer, D. (2010). A machine learning approach to predicting winning patterns in track cycling omnium. In Ifip international conference on artificial intelligence in theory and practice (pp. 67–76).
- Ofoghi, B., Zeleznikow, J., Macmahon, C., Rehula, J., & Dwyer, D. B. (2016). Performance analysis and prediction in triathlon. Journal of sports sciences, 34(7), 607–612.
- Richter, C., O’Reilly, M., & Delahunt, E. (2021). Machine learning in sports science: challenges and opportunities. Sports Biomechanics, 0(0), 1-7.
- Schumaker, R. P. (2013). Machine learning the harness track: Crowdsourcing and varying race history. Decision Support Systems, 54(3), 1370–1379.

- S. Jung, S. Hwang, H. Shin, and D. H. Shim, "Perception, Guidance, and Navigation for Indoor Autonomous Drone Racing Using Deep Learning," IEEE Robotics and Automation Letters, vol. 3, no. 3, pp. 2539–2544, Jul. 2018, doi: 10.1109/lra.2018.2808368. [Online]. Available: http://dx.doi.org/10.1109/lra.2018.2808368

- P. Adcock, C. M. Crewe, N. Grange and M. A. Passmore, "Performance predictions for a single seater junior formula electric racing car," IEE Colloquium on Systems for Electric Racing Vehicles, London, UK, 1993, pp. 8/1-8/7. https://ieeexplore.ieee.org/document/274603

- K. Peng, Y. Hai and Z. Heng, "Design and manufacture of small off-road racing car for national Baja auto race," 2022 5th World Conference on Mechanical Engineering and Intelligent Manufacturing (WCMEIM), Ma'anshan, China, 2022, pp. 192-198, doi: 10.1109/WCMEIM56910.2022.10021520. https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=10021520

- D. Bhatnagar and S. Urolagin, "Data Warehousing for Formula One (Racing) Popularity Rating Using Pentaho Tools," 2021 IEEE 6th International Conference on Computing, Communication and Automation (ICCCA), Arad, Romania, 2021, pp. 1-7, doi: 10.1109/ICCCA52192.2021.9666247. https://ieeexplore.ieee.org/document/9666247

- Y. . -N. Wang, C. . -Y. Tseng, Y. . -L. Huang and J. C. Leong, "Investigation of 2004 Ferrari Formula One race car wing effects," 2010 International Symposium on Computer, Communication, Control and Automation (3CA), Tainan, Taiwan, 2010, pp. 85-88, doi: 10.1109/3CA.2010.5533726. https://ieeexplore.ieee.org/document/5533726

- J. J. H. Paulides, L. Encica, T. F. Beernaert, H. H. F. van der Velden, A. G. P. Parfant, and E. A. Lomonova, "Ultra-light-weight high torque density brushless PM machine design: Considering driving-cycle of a four- wheel drive race car," 2015 Tenth International Conference on Ecological Vehicles and Renewable Energies (EVER), Mar. 2015, doi: 10.1109/ever.2015.7112931. http://dx.doi.org/10.1109/ever.2015.7112931

- M. R. Bonyadi, Z. Michalewicz, S. Nallaperuma, and F. Neumann, "Ahura: A Heuristic-Based Racer for the Open Racing Car Simulator," IEEE Transactions on Computational Intelligence and AI in Games, vol. 9, no. 3, pp. 290–304, Sep. 2017, doi: 10.1109/tciaig.2016.2565661. http://dx.doi.org/10.1109/tciaig.2016.2565661

- D. Loiacono et al., "The 2009 Simulated Car Racing Championship," IEEE Transactions on Computational Intelligence and AI in Games, vol. 2, no. 2, pp. 131–147, Jun. 2010, doi: 10.1109/tciaig.2010.2050590. http://dx.doi.org/10.1109/tciaig.2010.2050590

- *P. Cai, H. Wang, H. Huang, Y. Liu, and M. Liu, "Vision-Based Autonomous Car Racing Using Deep Imitative Reinforcement Learning," IEEE Robotics and Automation Letters, vol. 6, no. 4, pp. 7262–7269, Oct. 2021, doi: 10.1109/lra.2021.3097345.*

http://dx.doi.org/10.1109/lra.2021.3097345

- J. Betz et al., “Autonomous Vehicles on the Edge: A Survey on Autonomous Vehicle Racing,” IEEE Open Journal of Intelligent Transportation Systems, vol. 3, pp. 458–488, 2022, doi: 10.1109/ojits.2022.3181510.
  http://dx.doi.org/10.1109/ojits.2022.3181510

- N. A. Spielberg, M. Templer, J. Subosits, and J. C. Gerdes, “Learning Policies for Automated Racing Using Vehicle Model Gradients,” IEEE Open Journal of Intelligent Transportation Systems, vol. 4, pp. 130–142, 2023, doi: 10.1109/ojits.2023.3237977. .
  http://dx.doi.org/10.1109/ojits.2023.3237977

- F. C. Wykes, "Influence of electric vehicle racing formulae on electric competition vehicle systems," IEE Colloquium on Systems for Electric Racing Vehicles, London, UK, 1993, pp. 311-313.
  IEEE Xplore Full-Text PDF

- *P. Cai, H. Wang, H. Huang, Y. Liu, and M. Liu, “Vision-Based Autonomous Car Racing Using Deep Imitative Reinforcement Learning,” IEEE Robotics and Automation Letters, vol. 6, no. 4, pp. 7262–7269, Oct. 2021, doi: 10.1109/lra.2021.3097345. [Online].*
  http://dx.doi.org/10.1109/lra.2021.3097345

- S. Zwickl-Bernhard, J. Steiner, A. Pöllinger and G. Artner, "Carbon-Fiber Reinforced Antenna Cavity Hidden in the Monocoque of a Racing Car," 2018 IEEE 29th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), Bologna, Italy, 2018, pp. 1126-1127, doi: 10.1109/PIMRC.2018.8580704.
  https://ieeexplore.ieee.org/document/8580704

- S. Wu et al., "Design and Simulation of an Autonomous Racecar: Perception, SLAM, Planning and Control," 2021 IEEE International Conference on Autonomous Systems (ICAS), Montreal, QC, Canada, 2021, pp. 1-5, doi: 10.1109/ICAS49788.2021.9551125.
  https://ieeexplore.ieee.org/document/9551125