# **EXPERIMENT REPORT**

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| **Student Name** | Aibarna Singh Basnet |
| **Project Name** | AT1 |
| **Date** | 18/08/2023 |
| **Deliverables** | basnet\_aibarna-24585717-week1\_randomforest.ipynb  https://github.com/aibarna96/adv\_mla\_at1 |

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| 1. **EXPERIMENT BACKGROUND** | |
| Provide information about the problem/project such as the scope, the overall objective, expectations. Lay down the goal of this experiment and what are the insights, answers you want to gain or level of performance you are expecting to reach. | |
| **1.a. Business Objective** | Explain clearly what is the goal of this project for the business. How will the results be used? What will be the impact of accurate or incorrect results?  The goal of this project is to develop a predictive model that classifies basketball players as potential draft picks for the upcoming season based on specific attributes. The intended business outcome is to aid basketball teams in optimizing their player recruitment process by identifying prospects with higher draft potential. The model's accurate predictions will assist teams in efficiently allocating resources, forming strategically balanced rosters, and gaining a competitive edge. However, incorrect predictions could lead to misallocation of resources and missed opportunities for team improvement. The project's success lies in providing actionable insights for effective player selection, thereby enhancing team performance and overall success. |
| **1.b. Hypothesis** | Present the hypothesis you want to test, the question you want to answer or the insight you are seeking. Explain the reasons why you think it is worthwhile considering it,  We aim to investigate whether specific player attributes, such as scoring efficiency, defensive performance, and overall productivity, have a substantial impact on a basketball player's likelihood of being drafted in the next season. Our hypothesis suggests that these attributes play a crucial role in draft prospects. By exploring the correlations and predictive power of these attributes, we aim to uncover insights that could enhance player recruitment strategies. This investigation is worthwhile as accurate predictions could optimize resource allocation and inform recruitment decisions, ultimately contributing to team success. |
| **1.c. Experiment Objective** | Detail what will be the expected outcome of the experiment. If possible, estimate the goal you are expecting. List the possible scenarios resulting from this experiment. |

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| 1. **EXPERIMENT DETAILS** | |
| Elaborate on the approach taken for this experiment. List the different steps/techniques used and explain the rationale for choosing them. | |
| **2.a. Data Preparation** | Describe the steps taken for preparing the data (if any). Explain the rationale why you had to perform these steps. List also the steps you decided to not execute and the reasoning behind it. Highlight any step that may potentially be important for future experiments  For data preparation, we began by loading the training dataset and transforming column names to lowercase for consistency. We then selected relevant features with strong correlations to the target variable "drafted." As missing values were present, we filled them with zeros for simplicity. The data was split into features and the target variable, followed by a division into training and testing sets. To address class imbalance, we employed SMOTE to oversample the minority class. We standardized the features using StandardScaler to ensure model effectiveness. While we treated missing values by filling with zeros, other advanced techniques like imputing could be explored for improved data quality. Additionally, feature engineering, interactions, or polynomial features might enhance model performance. The rationale for these steps is to ensure data is suitable for model training and that the model is provided with relevant information. |
| **2.b. Feature Engineering** | Describe the steps taken for generating features (if any). Explain the rationale why you had to perform these steps. List also the feature you decided to remove and the reasoning behind it. Highlight any feature that may potentially be important for future experiments  For feature generation, we started by selecting attributes that we hypothesized to be relevant indicators of a player's draft potential, including scoring efficiency, defensive performance, and overall productivity metrics. We combined features such as "porpag" (points per offensive rebound), "dunksmade" (number of successful dunks), "dporpag" (defensive rebounds per offensive rebound), and others. We also engineered "midmade\_midmiss," which represents the ratio of successful mid-range shots to unsuccessful ones. To enhance interpretability, we normalized features using StandardScaler. However, we noticed multicollinearity between "dunksmade" and "dunksmiss\_dunksmade," leading us to remove the latter due to redundancy. Notably, "midmade" and "midmade\_midmiss" could be vital for future experiments as they might reflect a player's proficiency in mid-range shooting, an area of increasing importance in modern basketball strategy. |
| **2.c. Modelling** | Describe the model(s) trained for this experiment and why you choose them. List the hyperparameter tuned and the values tested and also the rationale why you choose them. List also the models you decided to not train and the reasoning behind it. Highlight any model or hyperparameter that may potentially be important for future experiments |

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| 1. **EXPERIMENT RESULTS** | |
| Analyse in detail the results achieved from this experiment from a technical and business perspective. Not only report performance metrics results but also any interpretation on model features, incorrect results, risks identified. | |
| **3.a. Technical Performance** | Score of the relevant performance metric(s). Provide analysis on the main underperforming cases/observations and potential root causes.  The classification results indicate a promising performance of the predictive model, with an accuracy of 98%. The precision for the positive class (drafted = 1) is relatively low at 0.28, implying that among the instances predicted as drafted, only around 28% are true positives. This low precision suggests that the model might have a tendency to produce false positives, possibly due to the class imbalance and the challenge of accurately identifying the small number of drafted players. The recall for the positive class is higher at 0.71, indicating that the model successfully captures a significant portion of the actual drafted players. The F1-score, which balances precision and recall, is at 0.40 for the positive class. The macro average F1-score is 0.70, indicating decent overall model performance. The AUROC score of 0.8456 suggests that the model has a good ability to distinguish between drafted and non-drafted players. To improve performance, it's crucial to address the imbalance issue and consider strategies to enhance precision without compromising recall. Further analysis of the underperforming cases might reveal specific patterns or characteristics contributing to misclassifications. |
| **3.b. Business Impact** | Interpret the results of the experiments related to the business objective set earlier. Estimate the impacts of the incorrect results for the business (some results may have more impact compared to others)  The experimental results showcase a promising performance of the predictive model in terms of accuracy (98%) and AUROC score (0.8456), indicating its ability to differentiate between drafted and non-drafted players. However, the precision for the positive class is relatively low at 0.28, implying a considerable number of false positives. While the model successfully identifies a significant portion of drafted players with a recall of 0.71, the overall precision-recall trade-off warrants further consideration. In the context of the business objective, the implications of incorrect predictions can be substantial. False positives could lead to the misallocation of resources, as teams may invest in players predicted to be drafted but who might not perform as expected. This could negatively impact team finances, strategy, and overall competitiveness. Additionally, false negatives (undrafted players predicted as drafted) may result in missing out on valuable talent, hindering team development. Hence, it is vital to enhance precision without sacrificing recall, ensuring more accurate predictions and mitigating potential negative impacts on team recruitment decisions and performance. |
| **3.c. Encountered Issues** | List all the issues you faced during the experiments (solved and unsolved). Present solutions or workarounds for overcoming them. Highlight also the issues that may have to be dealt with in future experiments.  During the experiments, several issues were encountered and addressed. The class imbalance between drafted and non-drafted players was mitigated using the Synthetic Minority Over-sampling Technique (SMOTE), which improved model performance. However, despite SMOTE, the precision for the drafted class remained relatively low, indicating challenges in correctly identifying drafted players. The multicollinearity between "dunksmade" and "dunksmiss\_dunksmade" was detected and resolved by removing the latter, enhancing model interpretability. Future experiments should focus on refining the precision-recall trade-off, potentially by exploring advanced sampling techniques or utilizing different algorithms tailored for imbalanced data. Additionally, the impact of including more diverse and detailed player attributes on model performance should be investigated, as certain attributes might have stronger predictive power for draft outcomes. Regular model updating and retraining using new data can address potential shifts in draft criteria and player attributes over time. |

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| 1. **FUTURE EXPERIMENT** | |
| Reflect on the experiment and highlight the key information/insights you gained from it that are valuable for the overall project objectives from a technical and business perspective. | |
| **4.a. Key Learning** | Reflect on the outcome of the experiment and list the new insights you gained from it. Provide rationale for pursuing more experimentation with the current approach or call out if you think it is a dead end.  The experiment's outcome provides valuable insights into the predictive capabilities of the model for identifying drafted basketball players. The experiment highlighted the challenges of achieving a balanced precision-recall trade-off, especially given the rarity of drafted players. The insights gained include the importance of refining the model's precision, investigating additional features, and exploring advanced techniques for handling class imbalance. Despite achieving a promising AUROC score and demonstrating potential for enhancing team recruitment, the limitations in precision call for further experimentation. The current approach is not a dead end; instead, it signals the need for iterative refinement. By conducting more experiments, testing alternative algorithms, and exploring diverse feature sets, the model's performance can likely be improved, offering more reliable predictions for player drafting and contributing to more effective decision-making in professional basketball team management. |
| **4.b. Suggestions / Recommendations** | Given the results achieved and the overall objective of the project, list the potential next steps and experiments. For each of them assess the expected uplift or gains and rank them accordingly. If the experiment achieved the required outcome for the business, recommend the steps to deploy this solution into production.  Potential Next Steps and Experiments:  1. \*\*Feature Engineering Refinement:\*\* Explore additional player attributes that might have a strong impact on draft outcomes, such as player statistics, team performance, and player rankings. Expected Uplift: Moderate. This step could lead to improved model performance by incorporating more comprehensive player profiles.  2. \*\*Algorithm Selection and Hyperparameter Tuning:\*\* Experiment with different classification algorithms (e.g., gradient boosting, support vector machines) and perform hyperparameter tuning to find the best model configuration. Expected Uplift: Moderate. Selecting the most suitable algorithm can enhance predictive accuracy and reliability.  3. \*\*Ensemble Methods:\*\* Investigate ensemble methods, such as stacking or blending multiple models, to leverage the strengths of different algorithms. Expected Uplift: Moderate. Ensemble methods can potentially yield more accurate and robust predictions.  4. \*\*Advanced Sampling Techniques:\*\* Explore advanced sampling techniques beyond SMOTE to further address class imbalance. Expected Uplift: Moderate. Leveraging state-of-the-art sampling methods could lead to better balance in precision and recall.  5. \*\*Temporal Analysis:\*\* Perform temporal analysis to determine if draft criteria have evolved over time, necessitating model updates. Expected Uplift: Low to Moderate. This could offer insights into the changing dynamics of player drafting.  6. \*\*External Data Integration:\*\* Incorporate external data sources, such as player background information and injury history, to enrich the dataset. Expected Uplift: Moderate. Additional context might improve the model's predictive power.  7. \*\*Domain Expert Consultation:\*\* Collaborate with basketball experts to gain insights into domain-specific factors that contribute to draft decisions. Expected Uplift: Low to Moderate. Expert insights could inform feature selection and model development.  Ranking and Recommendations:  Based on the potential next steps, the ranking and recommendations are as follows:  1. Feature Engineering Refinement  2. Algorithm Selection and Hyperparameter Tuning  3. Ensemble Methods  4. Advanced Sampling Techniques  5. Temporal Analysis  6. External Data Integration  7. Domain Expert Consultation  If the experiment achieved the required outcome for the business (high precision, recall, and F1-score), the next steps would involve deploying the solution into production. This would entail the following steps:  1. \*\*Model Deployment:\*\* Choose a production environment (e.g., cloud platform) and deploy the trained model to make real-time predictions.  2. \*\*Monitoring and Maintenance:\*\* Implement monitoring mechanisms to track model performance over time. Regularly retrain the model with updated data to ensure its relevance.  3. \*\*Integration:\*\* Integrate the model's predictions into the team's recruitment process, providing decision-makers with actionable insights.  4. \*\*Feedback Loop:\*\* Establish a feedback loop where the model's predictions and actual outcomes are continuously compared. This loop informs model refinement and improvements.  5. \*\*Continuous Improvement:\*\* Based on feedback and performance, iterate on the model by incorporating new insights, features, and techniques to enhance its accuracy and value to the business. |