**🏈 Examining the Factors Influencing Injuries in the NFL**

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**🔍 The Problem**

• NFL injuries are rising — with major medical & long-term consequences.

• Current predictive models are reactive, not proactive, and lack transparency.

• Goal: Predict injuries using machine learning and gain interpretable insights.

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| **📊 The Dataset**  • Injury Plays (2019–2020): 1,513 rows, 84 features  • Play-by-Play Data: 94,963 rows, 372 features  • Final merged set: 88,336 plays, 1,619 injuries  • Key Features: Down, Distance, Yard-line, Game Seconds Remaining (GSR), Weather, Team Factors |  |
|  | **🛠️ Feature Engineering**  • Domain Knowledge: 3rd & Long, Goal-line Situations  • External: Temperature, Precipitation  • Team: Rest Days, Strategic Positioning |

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**✅ Key Takeaway**

Combining machine learning with explainability tools can reveal hidden patterns in injury risk — even when prediction remains difficult.

**🧠 Approach & Modelling**

• Goal: Predict injury occurrence

• Started with baseline decision trees

• Advanced to ensemble models:

• Gradient Boosting performed best

• Accuracy: 59.6%, • Precision: 58.8%, • Recall: 61.7%

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**📌 Conclusion**

• Predicting injuries is extremely challenging

• Injury rarity limits model effectiveness

• Explainability yielded valuable insights

• Future Work: Incorporate more player-specific data

**🧾 Explainability**

• Returned to decision trees for interpretability

• Extracted decision rules across 3 folds

• Developed a scoring system for rule terms

• Derived Feature Importance Ranking