



NFL Tackle Probability Model

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Vince Lombardi

2× Super Bowl champion (I, II)
5× NFL champion (1961, 1962, 1965, 1966, 1967)
2× NFL Coach of the Year (1959, 1961)

“Football is two things. It’s blocking and **tackling.**”

What Is The Problem?

- **Current Tackling Evaluations Are Subjective**
 - Limited quantitative insights into **how and why** tackles happen or fail.
- **Need for a Data-Driven Approach**
 - How can we **quantify** the likelihood of a tackle happening?
 - Can we **predict** tackling outcomes based on player position, movement, and surrounding defenders?
 - How can teams **use this information** to improve defensive schemes and player positioning?
- **Gaps in Existing Models**



Problem: **SEVERE** Class Imbalance

- **Filter Out Distance Defenders**
 - Only want defensive players within 1 Yard of the ball carrier. (Median distance all tackles are made in)
- **Balance the dataset**
 - Take a smaller count of tackles and non tackle frames
- **Stratify the sampling of tackles and non tackles across plays**
 - Ensure each play is accurately represented in the data

Before:

Tackle Frames: 686,578

Non-Tackle Frames: **5,142,091**

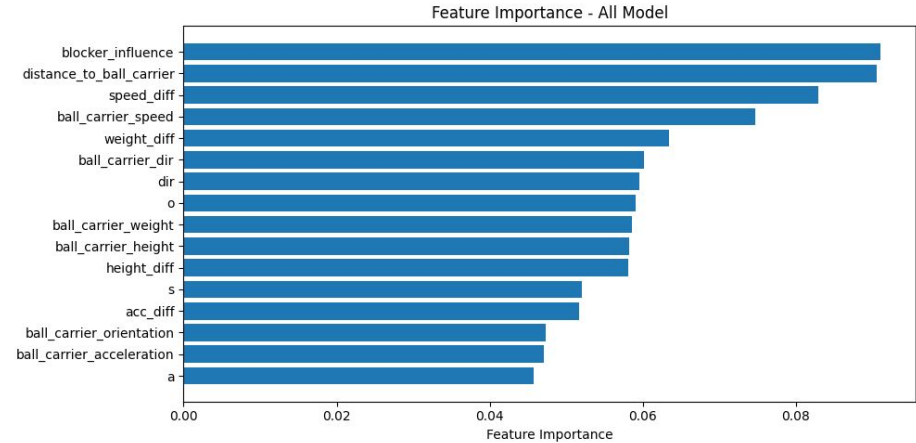
After:

Tackle Frames: **176,578**

Non-Tackle Frames: **106,788**

Feature Engineering

1. **Distance To Ball Carrier**
 - a. Find the **Euclidean Distance** between the defender and the ball carrier.
2. **Blocker Influence (Unique)**
 - a. Uses **exponential distance decay**, where closer blockers have a stronger effect on limiting a defender's movement.
3. **Height & Weight Difference (Unique)**
 - a. Modeled as a **scaling factor**, where larger size mismatches impact tackle success probability.



Josh Norman: 6'0, 194 lbs
Derrick Henry: 6'3, 247 lbs

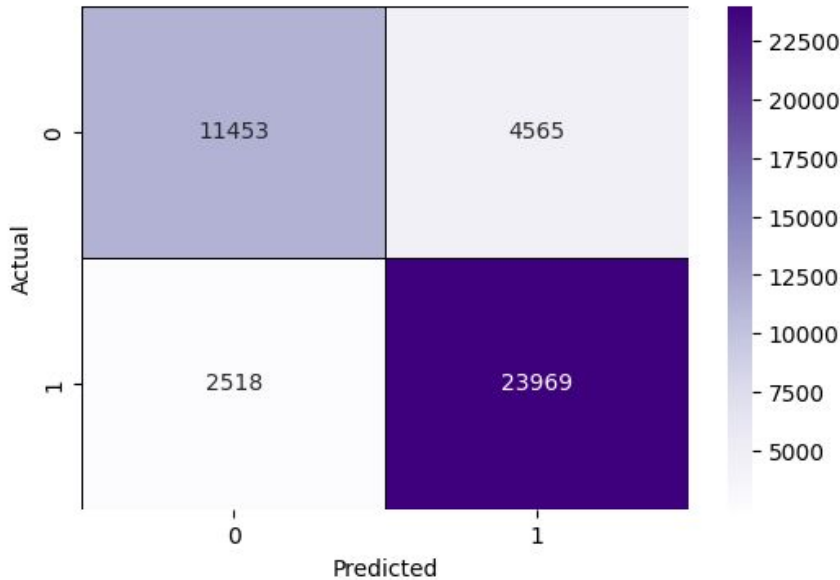
Model Architecture

- **XGBoost Model** – Gradient boosting with decision trees, optimizing errors iteratively.
- **Bayesian Optimization** – Hyperparameter tuning via **BayesSearchCV** for efficient search.
- **Regularization & Sampling** – Lasso and Ridge regression and feature subsampling to prevent overfitting.
- **Early Stopping & AUC** – Stops training if validation AUC plateaus.



Model Performance

Confusion Matrix for Model



- **Accuracy (83.33%)**: The overall percentage of correct predictions.
- **Precision (84.00%)**: When the model predicts a tackle, it is correct **84.00%** of the time.
- **Recall (90.05%)**: The model correctly identifies **90.05%** of all actual tackles.
- **F1-Score (87.12%)**: A balance between **precision and recall**, indicating strong overall model performance.

Key Takeaway:

- The model performs **consistently well across all metrics**, showing a good balance between **precision and recall**.

A Washington Redskins player, number 4, is shown in action, running with the ball. He is wearing a white jersey with maroon accents and a maroon helmet with a gold facemask. The background is a blurred crowd of spectators in a stadium.

Tackles Above Expected vs. Actual Tackles (Linebackers)

position

- OLB
- ILB
- MLB

Tackles Above Expected

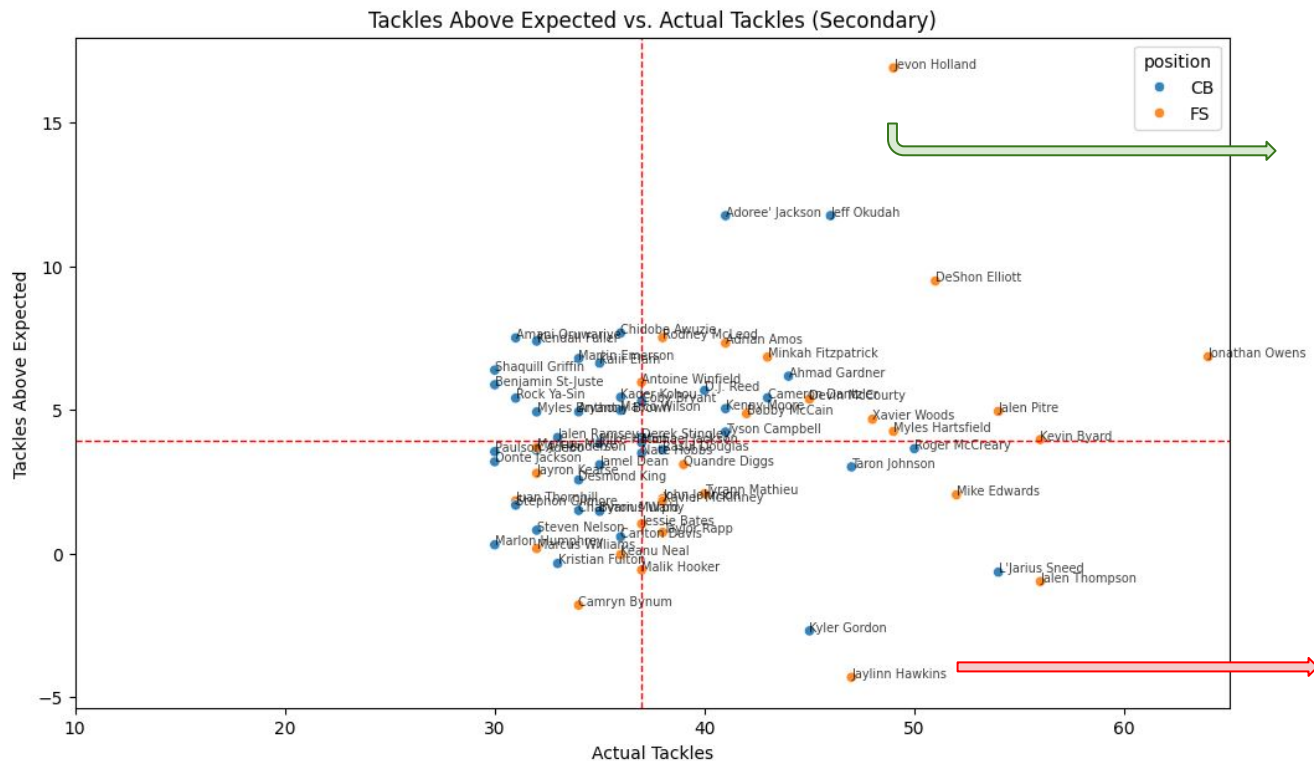
Actual Tackles

Key players and their approximate coordinates (Actual Tackles, Tackles Above Expected):

- Shaq Thompson (65, 10.5)
- Jordan Hicks (75, 10.5)
- Foyesade Oluokun (85, 10.5)
- Cole Holcomb (70, 9.5)
- Jordyn Brooks (85, 9.0)
- Pete Werner (75, 7.5)
- Bobby Okereke (70, 7.0)
- Divine Deablo (75, 6.5)
- Alex Singleton (65, 7.0)
- Frankie Luvu (45, 7.5)
- Denzel Perryman (40, 8.5)
- Patrick Queen (55, 5.5)
- Jerome Baker (50, 4.5)
- Devin Bush (45, 5.0)
- Uchenna Nwosu (35, 5.0)
- Sione Takitaki (35, 4.5)
- Quay Walker (60, 4.0)
- Bobby Wagner (65, 3.5)
- David Long (65, 3.0)
- Kyzir White (55, 2.0)
- Mykal Walker (70, 2.0)
- T.J. Edwards (75, 2.0)
- Zaire Franklin (85, 2.0)
- Brian Burns (30, 2.5)
- Akeem Davis-Gaither (35, 2.5)
- Favon Walker (30, 2.0)
- Matt Milano (35, 1.5)
- Stemiah Owusu-Koramoah (40, 1.5)
- Darius Harris (30, 1.0)
- Josey Jewell (35, 0.5)
- Quincy Williams (50, -1.0)
- Logan Wilson (50, -1.0)
- DeAndre Campbell (65, 0.0)
- Nick Bolton (70, 0.0)
- Bonuan Smith (85, 0.0)
- C.J. Mosley (85, -1.0)
- Rashaan Evans (85, -2.0)
- Malcolm Rodriguez (45, -2.0)
- Jacob Phillips (45, -3.0)
- Demario Davis (45, -6.0)
- Amin Davis (45, -7.0)
- Dre Greenlaw (50, -5.0)
- Elandon Roberts (55, -5.0)
- Germaine Pratt (60, -7.0)
- Devin White (65, -7.0)
- Eric Kendricks (65, -7.0)
- Devin Lloyd (70, -6.5)
- Tholias Momoa (65, -4.0)
- Ernest Jones (60, -4.0)
- Anthony Barr (30, -3.5)
- Tae Crowder (35, -5.5)
- Jonas Griffith (40, -2.0)
- Kenneth Murray (35, -1.5)
- Kamu Grugier-Hill (35, -1.0)
- Whaun Bentley (50, -2.0)
- Fred Warner (55, -3.0)
- Alex Anzalone (65, -4.5)
- Myles Jack (70, -3.0)

A photograph of Minnesota Vikings defensive end Danielle Hunter in action on the field. He is wearing his white home jersey with purple accents and the number 54. He is in a three-point stance, ready for the play to start. The background is a blurred view of the stadium and other players.

Model Insights (Secondary)



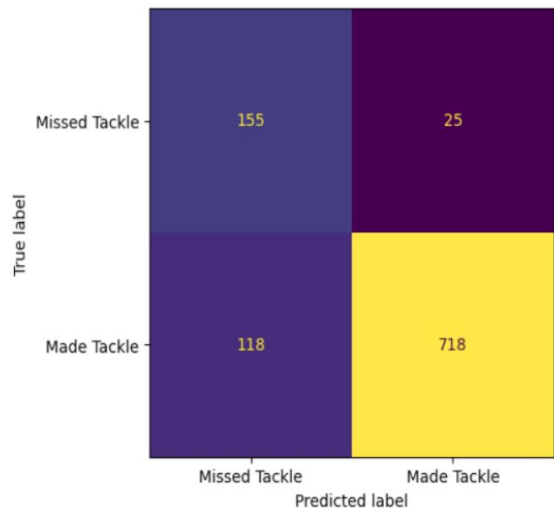
Jevon Holland



Jaylinn Hawkins

Other Models Comparisons

(Uncovering Tackle Opportunities and Missed Opportunities)



Class	Precision	Recall	F1-Score
Made Tackle	0.97	0.86	0.91
Missed Tackle	0.57	0.86	0.68

“We generated the training dataset with 8000 made tackles and 1583 missed tackles from weeks 1-8 tracking data...The test dataset includes 836 made tackles and 180 missed tackles exclusively from week 9 to prevent leakage.”

1. **Frame-Level Data Captures More Context** – Tracks player movement, positioning, and decision-making across time, unlike their play-based approach.
2. **Improved Temporal Dynamics** – Models real-time reactions and adjustments, providing deeper insights into tackle success vs. failure.
3. **More Data, Better Generalization** – 200,000 frames improve learning, while their limited sample (~9,819 plays) risks overfitting.

Balanced Dataset Advantage

- Prevents **bias toward tackles** (their 5:1 ratio skews predictions).
- Improves **missed tackle detection**, crucial for defensive evaluation.
- Enhances **model stability**, avoiding trivial predictions.

Why My Model Is Unique

- ✓ **Frame-Level Analysis** – Evaluates every **moment leading up to the tackle**, not just final outcomes.
- ✓ **Beyond Proximity** – Identifies **why** some defenders **miss tackles even when close**, using movement, angles, and ball carrier characteristics.
- ✓ **Balanced Dataset** – Prevents bias by focusing on relevant moments, ensuring **missed tackles are properly learned**, unlike models that overpredict tackles.
- ✓ **Predictive, Not Reactive** – Unlike models that **only detect tackles happening**, this model **forecasts tackle success** before impact.

Model Applications & Next Steps

- **Player Evaluation & Scouting** – Identifies defenders who consistently **maximize tackle opportunities** and those who struggle, helping teams with **talent evaluation**.
- **Coaching & Player Development** – Pinpoints **why tackles are missed** (e.g., bad angles), allowing for **targeted training** to improve tackling efficiency.
- **Game Strategy & Defensive Schemes** – Helps coaches understand **which defenders perform best in specific scenarios**, optimizing defensive assignments and formations.

