## **WORKSHOP #1**

# KAGGLE SYSTEMS ENGINEERING ANALYSIS – NFL IMPACT DETECTION

#### **INTEGRANTS**

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SYSTEMS ANALYSIS & DESIGN

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# 1. Competition Overview

#### Goal:

The competition aims to accurately detect moments when NFL players make contact during plays. This involves developing models that can identify player-to-player or player-to-ground contacts reliably.

#### **Dataset Structure:**

- **Tracking Data:** Detailed numerical records capturing player positions, speeds, and accelerations at various time intervals.
- **Video Data:** Clips capturing game plays from multiple angles, providing visual context for player interactions.
- **Contact Labels:** Binary indicators that mark whether a contact occurred at a given moment between players or between a player and the ground.

## **Significant Constraints:**

- **Data Synchronization:** The need to align tracking data with video footage accurately poses a major challenge.
- **Data Quality Variability:** Variations in video quality (resolution, camera angles) and potential inaccuracies in tracking data can affect model performance.
- Threshold Determination: Defining what constitutes a "contact" requires careful tuning of thresholds, as small errors may lead to false positives or negatives.

# 2. Systems Analysis Report

### Systemic Analysis

### **Elements:**

Video Footage

Importance: The primary data source for detecting player interactions and collisions. It provides visual context for identifying contact events.

Player Tracking Data

Importance: Captures player positions and movements, enabling precise analysis of trajectories and proximity to other players

- Computer Vision for Player Detection and Motion Tracking Importance: Identifies player positions and movements in video frames, forming the basis for collision detection.
- Machine Learning Models for Contact Classification

Importance: Uses historical data to classify contact events, distinguishing between real collisions and false positives

submission.csv File with Contact Predictions

Importance: The result submitted to the competition contains predictions of player contacts based on the model's analysis.

Visualizations (Heatmaps, Overlays)

Importance: Helps interpret model outputs by visually highlighting contact zones and player interactions.

### Relationships:

- **Data Integration:** Tracking and video data must be synchronized to create a coherent representation of each play.
- Model Inputs: The combined data sources feed into the models, where the relationship between player movements (from tracking data) and visual cues (from video data) informs the detection of contacts.

• **Feedback Loop:** Errors in detection (due to misalignment or noise) can affect model training and lead to iterative improvements in threshold settings and data preprocessing.

# 1. System Objective

The **main objective** of the system is:

"To accurately detect and analyze physical contacts between NFL players using sensor, tracking, and video data in order to improve player safety, officiating accuracy, and performance evaluation."

In this context, the **output** of the system is a structured prediction of contact events, enriched with contextual data.

# 2. System Elements

The system is composed of interrelated components. These can be grouped into three major categories:

## 2.1. Inputs (Raw data the system ingests)

- **Players** The physical agents being monitored on the field.
- **Sensor and Tracking Data** Real-time information on player position, speed, and acceleration.
- Video Data Game footage from multiple camera angles.
- Contact Labels (Ground Truth) Human-annotated contact events used for training and validation.
- **Environmental Conditions** Weather, lighting, and field quality, which can impact visibility and data accuracy.

#### 2.2. Processing (How the data is analyzed)

• **Computer Vision Models** – Analyze video footage to identify possible contacts visually.

- Machine Learning Models Predict contact events based on data patterns and trained labels.
- **Sensor-Video Fusion** Combine tracking and video data for more accurate detection.
- **Contact Thresholds** Rules for determining what counts as significant contact (e.g., force, proximity, duration).

#### 2.3. Outputs (What the system produces)

- **Contact Predictions** Binary or probabilistic indicators of whether contact occurred at a given time between players.
- Contact Reports Aggregated statistics on number, type, and intensity of contacts.
- **Visualizations** Heat maps, contact replays, or graphical overlays for better understanding.

# 3. System Relationships

#### 3.1. Input → Processing

- Sensor data is fed into machine learning models, providing temporal and spatial context for player movement.
- Video data is processed by computer vision systems, often synchronized with sensor data.
- Ground truth labels are used to train and validate predictive models.
- **Data of players** are used to additional entry data useful for better training behavior of Machine Learning.
- External conditions are in mind for any anormal changes of data.

#### 3.2. Internal Processing Interactions

- Fusion techniques combine video and sensor data to handle uncertainties and missing information.
- Model performance depends on well-calibrated thresholds for distance, speed, and direction to flag a contact.
- Algorithms continuously learn and update, based on feedback from predictions and real-world outcomes.
- Sensor and Tracking Data and analyze of videos are merged for to interpretation of Machine Learning

### 3.3. Processing → Outputs

- Predicted contacts are turned into structured data reports, usable by analysts and teams.
- Visualizations and replays enhance communication of complex data insights.
- System decisions can adjust in real time, improving accuracy as feedback is processed.

Representation diagram and GitHub folder: https://github.com/ltzNxhin/SAD---Nahin-Nicolas-and-Anderson/blob/main/Workshop1%20-%20Kaggle/SystemE%26R.png.

# Complexity & Sensitivity

# Complexity

#### Multimodal Data Integration:

- Data Sources & Integration:
  - The system integrates sensor data (tracking player positions, speeds, accelerations) with video footage from multiple cameras.
  - *Analysis:* Because it must combine quantitative (sensor) and qualitative (video) data, and align them in time, the system is inherently complex.
  - Example: Aligning sensor readings at 100 Hz with video captured at 30 fps requires sophisticated synchronization algorithms.

#### • Temporal Alignment:

- Short-Duration Events:
  - Contact events occur in fractions of a second, so even a 0.1-second delay can lead to misinterpretation of events.
  - Analysis: The need for precise temporal matching adds complexity because the system must coordinate data streams with millisecond accuracy.
  - Example: A rapid player collision could be missed or mis-timed if sensor and video data are not perfectly synchronized.

# • Spatial Dynamics:

- Dynamic Player Movements:
  - Players move rapidly and unpredictably across the field.
  - *Analysis:* The complex spatial interactions and non-linear trajectories among many moving elements (players) increase system complexity.
  - Example: Two receivers crossing paths during a deep pass require advanced spatial modeling to determine if contact occurred.

# • Class Imbalance and Rare Events:

### Detection Challenges:

- Most game frames do not show contact events, making the events rare compared to non-events.
- *Analysis:* The system must focus on detecting infrequent contacts within thousands of frames, which demands sophisticated classification methods and makes the system more complex.
- Example: If a dataset has 10,000 frames with only 300 collisions, the model must be finely tuned to avoid false positives while detecting the rare events.

### Data Uncertainty and Noise:

### Variability and Error Correction:

- Noise from sensor readings, video quality fluctuations, and inconsistent ground truth labels all contribute to uncertainty.
- Analysis: The presence of multiple, variable data sources (each with its own noise and error patterns) multiplies the number of relationships the system must manage, adding to its complexity.
- Example: Sensor drift over time or variations in video quality due to weather conditions require robust error-correction techniques.

# • Real-Time Processing Demands:

#### Continuous Data Streams:

- The system must process data in real time, which imposes strict computational and timing constraints.
- *Analysis:* Real-time operation increases complexity because the system must continuously and efficiently process large volumes of data without delay.
- Example: Live game data processing for immediate contact detection demands high computational power and optimized algorithms.

The system is quite complex because it comprises many interrelated elements, multiple data sources, precise temporal-spatial alignment, complex modeling of rare events, and real-time processing requirements. Each relationship between these elements adds a layer of interdependency, further increasing complexity.

# Sensitivity

#### • Sensor Accuracy:

## Measurement Precision:

- Small inaccuracies in sensor data can lead to misclassifications of contact events.
- *Analysis:* The system's performance is highly sensitive to the precision of sensor inputs, making it critical to maintain high calibration standards.

• Example: A slight positional error may incorrectly classify a near miss as a collision, impacting the system's reliability.

### Video Quality and Frame Rate:

### Impact on Visual Detection:

- High-definition, high frame rate footage allows for capturing subtle interactions; lower quality can obscure them.
- *Analysis:* Variability in video quality significantly affects the system's output, making it sensitive to external factors such as lighting and camera resolution.
- Example: A 60 fps, high-definition video can capture a slight brush between players that might be missed by a 24 fps, lower resolution camera.

# Synchronization Accuracy:

### Temporal Matching:

- Precise alignment of sensor and video data is essential; even a few milliseconds of misalignment can lead to errors.
- *Analysis:* The system is extremely sensitive to synchronization errors, as these errors propagate through the processing stages and affect final predictions.
- Example: A misalignment of 5 milliseconds in high-speed plays can lead to either false positives or missed collisions.

# Threshold Settings for Contact Detection:

#### Defining a Contact:

- Thresholds such as distance or impact force determine what qualifies as a contact event.
- Analysis: Small adjustments in these thresholds can drastically shift the balance between false positives and false negatives, highlighting the sensitivity of the system's decision criteria.
- Example: Changing a distance threshold from 1.5 meters to 1.3 meters might trigger a surge in false alarms during fast-paced plays.

The system is highly sensitive because even slight variations in sensor accuracy, video quality, synchronization, or threshold settings can lead to significant differences in detection outcomes. This sensitivity demands rigorous calibration, precise data alignment, and continuous monitoring of input parameters.

## Potential Constraints, Conflicts, or Points of Variability

Data Integration and Synchronization Challenges:

#### Multimodal Fusion Constraints:

- Integrating sensor data with video footage requires precise temporal and spatial alignment.
- *Analysis:* Misalignment between these data sources can lead to conflicts in event detection, making the system more susceptible to errors.
- Example: A misalignment between a 100 Hz sensor and a 30 fps camera can cause the system to incorrectly map player movements to the wrong video frames.

# Sensor Data Quality Variability:

#### Hardware and Noise Issues:

- Sensor drift, calibration issues, and electromagnetic interference can degrade data quality.
- *Analysis:* Variability in sensor performance, due to hardware differences or environmental factors, directly affects the reliability of contact detection, presenting a significant constraint.
- Example: A sensor on a player's helmet that drifts over time may result in gradually inaccurate position data.

# Video Data Variability:

#### Environmental Influences:

- Variability in video quality due to lighting conditions, weather, and camera angles can affect feature extraction.
- *Analysis:* Such variability introduces conflicts in the detection process, as the system must adapt to changing visual inputs that may not consistently capture key contact details.
- Example: A night game with poor lighting might produce shadowed areas, reducing the clarity of player interactions.

### Threshold Settings and Definition Conflicts:

#### Defining and Tuning Contact Criteria:

- Establishing thresholds for what constitutes a contact event is subjective and may vary between scenarios.
- *Analysis:* The system's performance can be inconsistent if the threshold settings are not dynamically adaptable to different game conditions, leading to either false positives or missed detections.
- Example: A fixed threshold might work well in one game scenario but fail in another where players are moving at different speeds or in more compact formations.

#### External Environmental Factors and Game Dynamics:

#### Impact of Real-World Conditions:

• External factors such as weather, field conditions, and game strategy

contribute to data variability.

- *Analysis:* These external variables add layers of uncertainty and unpredictability, which further constrain the system's performance.
- Example: A wet field might change the way players move, while rain can degrade video quality, leading to unexpected variations in detection accuracy.

The system faces numerous constraints, conflicts, and variability points due to the diverse and dynamic nature of real-world inputs. These factors must be managed carefully, as each source of variability—from data integration issues to environmental influences—can significantly affect the system's reliability and accuracy.

### Conclusions

The system developed to detect contact events in NFL games stands out for its advanced integration of tracking and video data, supported by computer vision and machine learning models. This multimodal approach enables accurate and context-rich detection of collisions, contributing to improved player safety, officiating accuracy, and performance analysis. Key strengths include real-time processing capabilities, the generation of interpretable outputs through visualizations and reports, and adaptability to new scenarios through trainable models and adjustable thresholds.

However, the system faces important limitations. Its technical complexity requires precise synchronization between data sources with different frequencies and qualities, making it highly sensitive to misalignment, noise, and environmental variability. Performance also heavily depends on video quality and sensor precision, while detecting rare contact events presents challenges due to class imbalance. Therefore, although the system offers a powerful and sophisticated solution, its final effectiveness relies on rigorous management of these critical factors.