

NextKick: Football Player Analysis Tool Using Machine Learning

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Abstract— Identifying grassroots football talent remains a persistent challenge due to the lack of structured scouting systems, limited access to professional evaluators, and the absence of reliable digital tools for skill assessment. Young players, especially from remote and underrepresented regions, often miss opportunities because clubs rely on manual scouting, subjective judgment, and inconsistent evaluation processes. Existing digital platforms either depend on costly infrastructure, require continuous internet connectivity, or fail to validate the authenticity and relevance of submitted performance videos.

To address these limitations, this project introduces NextKick, an AI-driven, mobile-centric scouting and talent-assessment platform designed specifically for real-world football environments. NextKick incorporates a lightweight Convolutional Neural Network (CNN) pipeline capable of analyzing player performance videos, tracking player motion, and validating whether the uploaded content matches required football-specific criteria. This automated verification prevents irrelevant or misleading submissions while ensuring fairness and transparency in the scouting process. The platform further empowers clubs through an integrated admin evaluation module, allowing them to accept or reject players and directly communicate the selection outcome along with the identifying club.

Beyond assessment, NextKick enhances accessibility by offering intuitive UI workflows, standardized skill-test formats, and scalable backend services optimized for low-bandwidth regions. Initial testing indicates that the system delivers accurate motion tracking and rapid video classification while maintaining computational efficiency suitable for common smartphone hardware.

By merging lightweight AI analytics, structured digital scouting, and democratized access to opportunities, NextKick establishes a modern, inclusive pathway for football talent discovery. The system supports ethical talent identification, reduces scouting bias, and enables clubs to build stronger youth pipelines through data-backed insights.

Index Terms— Football Talent Scouting, Motion Tracking, Convolutional Neural Networks, Video Classification, Player

Evaluation Systems, AI-Driven Sports Analytics, Lightweight Models, Grassroots Football Development

I. INTRODUCTION

Football has become one of the fastest-growing sports ecosystems in India, with increasing participation at grassroots levels and expanding opportunities across academies, clubs, and state associations. Despite this growth, the pathway for young players to showcase their skills remains fragmented and inaccessible, especially for athletes coming from rural regions, small towns, and economically disadvantaged backgrounds. Traditional scouting methods still rely heavily on physical trials, limited outreach programs, and subjective evaluation by individual scouts. As a result, thousands of talented players fail to receive timely exposure, creating a widening gap between potential and opportunity.

The core challenge in modern talent discovery lies in the absence of standardized, scalable, and transparent scouting mechanisms. Clubs and academies often conduct trials infrequently and in specific locations, making it difficult for players from remote or low-resource environments to participate. Even when trials are available, skill evaluation depends on human observation, which can be biased, inconsistent, or influenced by environmental factors such as crowd size, fatigue, or weather conditions. This lack of accessible and objective assessment prevents many players from being noticed at the right time and hinders the development of a structured national talent pipeline.

Digital solutions have attempted to bridge this gap by allowing players to upload performance videos or maintain online portfolios. However, most existing platforms fail to validate whether submitted videos are authentic, football-relevant, or compliant with standardized drill formats. Many depend on high-speed internet, cloud-based computation, or expensive infrastructure—making them impractical for widespread use in regions with inconsistent connectivity. Additionally, these solutions often provide only visibility, not actionable insights, and lack a robust mechanism for clubs to evaluate, accept,

reject, or communicate with aspiring players in a professional manner.

Advancements in computer vision, deep learning, and AI-driven motion analysis offer a transformative opportunity to automate and democratize football scouting. Research in this domain shows promising results in pose estimation, skill recognition, and movement pattern analysis. However, most models require high computational resources or server-dependent processing, limiting real-world scalability. There remains a clear need for an accessible, lightweight, mobile-first system capable of evaluating skill videos quickly, accurately, and without reliance on continuous network access.

To address these challenges, this project introduces NextKick, an AI-powered, mobile-centric football scouting platform engineered for real-world conditions faced by young athletes and local clubs. NextKick integrates a lightweight Convolutional Neural Network (CNN) and motion-tracking pipeline capable of analyzing uploaded videos, identifying football-specific movements, and rejecting irrelevant or fraudulent submissions. By running efficiently on commonly available smartphones and low-end devices, the system ensures inclusivity across diverse socioeconomic backgrounds.

In addition to automated analysis, NextKick offers a structured club evaluation framework, enabling authorized scouts and administrators to review player submissions, approve or reject applications, and clearly indicate which club has accepted the player. This transparent communication flow helps standardize scouting practices and reduces uncertainty for aspiring athletes. The platform's intuitive UI, multilingual support, and simplified skill-test guidelines further enhance usability for players with varying levels of digital experience.

The objective of this project is to build a scalable, reliable, and transparent talent identification system that lowers the barriers to entry into professional football. By combining lightweight AI models, automated video validation, and structured club-player interactions, NextKick aims to modernize the scouting ecosystem, reduce bias, and provide equal opportunities to players nationwide. The system aligns with broader goals of sports development, digital inclusion, and data-driven talent management, offering a step toward a more organized and equitable footballing future.

II. LITERATURE SURVEY

Recent advancements in machine learning, deep learning, and real-time video analytics have significantly influenced the development of intelligent sports systems. Various studies have explored performance prediction, player identification, action tracking, and object detection—laying the foundation for AI-driven scouting platforms like NextKick.

Early research focused heavily on using statistical learning for predicting player performance across sports. Rajeswari et al. (2024) developed machine learning models, including naïve Bayes and linear regression, to forecast player output in cricket, kabaddi, and hockey using historical metrics such as runs, outs, wins, and fitness records. Their work emphasizes the importance of structured data, feature selection, and dashboard visualization, highlighting how ML models can support decision-makers in team selection processes.

While valuable, these approaches rely on numerical data rather than video-based assessments, limiting real-world applicability for football skill scouting.

Deep learning-based methods have gained prominence for tasks involving video understanding and object tracking. Wojke et al. introduced DeepSORT, a real-time multi-object tracking framework that integrates appearance embeddings with motion modeling to reduce identity switches and improve long-term tracking accuracy.

Their method demonstrates how CNN-based appearance descriptors can significantly enhance reliability in video-based tracking—an approach directly relevant to NextKick's requirement for accurate player identification and continuous motion tracking in football clips.

Object detection has also evolved through increasingly optimized architectures. The YOLO family of models, reviewed extensively by Rejin Varghese and Sambath (2024), presents major improvements in speed, robustness, and small-object recognition. YOLOv8, in particular, integrates attention mechanisms, dynamic convolution, and efficient feature fusion to achieve superior detection performance across diverse video scenarios.

Such advancements make YOLO-based models suitable for validating whether an uploaded video is truly football-related, ensuring that users submit only relevant and standardized content.

Similarly, foundational literature on Convolutional Neural Networks (CNNs) by O'Shea and Nash (2015) explains the operational structure of CNNs, including convolutional layers, receptive fields, and feature extraction techniques central to image and video classification tasks. Their insights support the architectural choices behind NextKick's lightweight CNN models for skill-based video analysis.

Additionally, studies focusing on web frameworks and performance optimization highlight the relevance of scalable deployment. Patel (2023) discusses how technologies like Next.js improve performance, reduce latency, and enhance user accessibility through optimized rendering and image handling techniques.

These findings reinforce NextKick's decision to adopt a high-performance frontend framework capable of efficiently handling video uploads, dashboards, and multilingual interfaces.

Across the literature, a recurring theme emerges: the need for systems that combine real-time tracking, lightweight models, robust detection, and practical deployability. However, none of the existing studies address the specific challenge of validating football-specific videos or providing a transparent acceptance/rejection workflow for clubs, which are key contributions of NextKick.

Author & Year	Method Used	Key Findings	Limitation
Rajeswari et al. (2024)	ML models (Naïve Bayes, Linear Regression)	Accurate prediction of player performance using historical metrics	Does not process videos; cannot evaluate real football skills
Varghese & Sambath (2024)	YOLOv8 Object Detection	High-speed, high-accuracy detection suitable for real-time tasks	Not tailored for sports-specific actions or player drills
Wojke et al. (2017)	Tracking-by-Detection + Appearance Embeddings	Effective long-term tracking with reduced identity switches	Requires strong detectors; not directly skill-assessment oriented
O'Shea & Nash (2015)	CNN Theory & Architecture	High accuracy with optimized efficient models	Heavy for low-end devices; not suitable for offline rural deployment

III. METHODOLOGY

The methodology followed in this research consists of a structured sequence of stages designed to develop a lightweight, AI driven football talent assessment system capable of validating user submitted videos, tracking player movement, and supporting club-level player selection. The workflow begins with the acquisition and preprocessing of football related video data, followed by the design and integration of detection, tracking, and classification models, and concludes with system optimization and deployment using

a performance enhanced web interface. Each component of the methodology is carefully constructed to ensure that NextKick operates reliably under real world conditions, particularly when videos are captured on mobile devices with inconsistent lighting, motion, and background variations.

The first stage involves collecting and preprocessing raw video samples. The dataset comprises publicly available match footage, curated football skill demonstration clips, and user-recorded smartphone videos to capture natural variability in video quality. All videos are standardized to a uniform frame rate and resolution to maintain consistency during feature extraction. Preprocessing includes stabilization, brightness normalization, and cropping to reduce background interference and emphasize the player and ball. Because mobile-recorded football videos often suffer from motion blur, uneven camera movement, and cluttered surroundings, augmentation techniques such as perspective distortion, brightness shifts, rotation, and motion blur simulation are applied. These steps enhance model robustness and align with real-world challenges identified in multi-object tracking literature such as DeepSORT, which emphasizes the need to account for occlusions and noisy detections in uncontrolled environments. Class balancing is also implemented to ensure that all skill categories such as dribbling, shooting, passing, and juggling are proportionally represented.

The second stage focuses on designing the detection subsystem using a YOLOv8-based architecture. YOLOv8 was selected due to its strong real-time performance, its ability to detect small objects such as footballs, and its enhanced feature extraction mechanisms, including dynamic convolution and attention-driven modules that improve robustness in complex scenes, as noted by Varghese and Sambath (2024)

The detector identifies key elements in each video frame, including the player, the football, and spatial movement cues. The detections serve as the basis for all subsequent tracking and classification stages. To support efficient inference on consumer-grade devices, the detection model undergoes pruning and quantization, reducing computational overhead without compromising accuracy.

Following detection, player tracking is implemented using a DeepSORT-based framework. DeepSORT extends traditional SORT tracking by incorporating deep appearance descriptors that help maintain identity consistency across frames, even when the player changes orientation, temporarily exits the frame, or becomes partially occluded. This integration of motion prediction via a Kalman filter and appearance based matching addresses limitations of simple IoU-based tracking and significantly reduces identity switches, as demonstrated by Wojke et al. (2017)

The tracking module generates stable trajectories and movement profiles, enabling the extraction of important temporal features such as speed variations, ball-contact patterns, and directional changes. These motion features serve as inputs for downstream skill classification.

The fourth stage involves training lightweight convolutional neural networks to classify football-specific skills. Drawing on

the theoretical foundations of CNNs described by O'Shea and Nash (2015)

the classifier architecture is optimized using receptive field tuning, depth-wise convolutions, and compact feature extraction layers to maintain a small computational footprint. Each classifier processes cropped player-centric sequences produced by the detection and tracking stages. The system not only evaluates skill execution such as dribbling control, shooting mechanics, and juggling consistency but also incorporates a Video Validation Module. This module automatically determines whether the submitted video follows the expected drill structure, contains a visible football, maintains a clear focus on the player, and meets minimum quality thresholds. Detection and tracking outputs are cross-referenced to reject irrelevant or fraudulent videos before they enter the evaluation pipeline, making this component a novel contribution within the domain of football talent scouting.

Model training and optimization follow established deep learning practices. Loss functions such as cross-entropy are used for classification tasks, while tracking performance is evaluated through IDF1 scores and identity-switch counts. Hyperparameters are tuned experimentally to balance accuracy, speed, and generalization capability. Quantization and pruning are applied to the final models to enable smooth real-time inference on typical smartphones and laptops.

The final stage of the methodology involves deploying the system through a Next.js-based interface. Drawing on the performance optimization techniques outlined by Patel (2023), the frontend incorporates server-side rendering, code splitting, and image/video optimization strategies to reduce latency and improve accessibility for users in low-bandwidth environments. The interface supports multilingual features, efficient video upload handling, and a dashboard inspired by data presentation methods in sports analytics research such as that of Rajeswari et al. (2024). The platform also includes an administrative module where clubs can review analyzed submissions, accept or reject players, and communicate decisions through a structured workflow.

Overall, this methodology integrates robust video analysis models with a lightweight, user-friendly deployment environment to create a comprehensive football scouting system. By combining detection, tracking, skill classification, and automated video validation while ensuring efficient frontend delivery, NextKick bridges the gap between grassroots talent and professional scouting infrastructures.

IV. PERFORMANCE METRICS

To understand how well the NextKick system performs in real situations, its effectiveness was examined from two major angles: how accurately it interprets football actions and how efficiently it runs on typical user devices. The first part of the evaluation focuses on the model's ability to correctly recognize and validate football skills in uploaded videos. While overall Accuracy provides a basic indication of correct predictions, it is not sufficient by itself because the dataset

does not contain equal amounts of every skill type. Some skills, like dribbling, appear far more often than others, which means the model could seem accurate even if it struggles with the less common actions. For this reason, the F1-Score becomes far more meaningful, as it accounts for both Precision and Recall. A strong F1-Score shows that the system is not only making correct predictions but is doing so consistently across both frequently and infrequently occurring skill categories.

Along with these metrics, confusion matrices were studied to understand in detail where the model performs well and where it tends to make mistakes. These matrices reveal which actions the model sometimes mixes up, such as mistaking a controlled tap for slow-paced dribbling or confusing the first steps of a pass with a shot attempt. These insights make it easier to identify where additional data or better preprocessing may be needed. They also highlight situations in which the model struggles—such as when videos are shaky, poorly lit, or recorded at odd angles—providing a clear direction for improving future versions of the system.

Accuracy alone, however, is not enough for a system like NextKick, which must also run smoothly on a wide range of devices. Because users typically upload videos from their own phones, the system needs to process these videos quickly and with minimal strain on hardware. To evaluate this aspect, metrics such as inference speed, memory usage, and model size were considered. After model optimization and quantization, the detection and tracking components were able to process frames in real time on mid-range CPUs, allowing uploaded videos to be analyzed almost immediately. This responsiveness is essential because long delays would discourage players and scouts from using the platform. Storage and RAM consumption were also monitored to ensure that the system remains lightweight enough for widespread use without requiring high-end devices.

When combined, these evaluations show that NextKick delivers both reliable predictions and practical performance. The system is fast enough to handle real user videos, stable enough to track players throughout the clip, and accurate enough to differentiate between various football skills. This balance of accuracy and efficiency makes it well-suited for grassroots scouting, where players rely on everyday mobile devices and clubs need quick, trustworthy assessments.

V. IMPLEMENTATION

The implementation of the NextKick system brings together computer vision, deep learning, and a user-friendly web interface to create a scouting tool that works smoothly across a wide range of devices. The platform is built with a mobile-focused design philosophy so that players can upload videos and receive analysis without needing specialized hardware or strong internet connectivity. At the center of this implementation is a highly optimized web application built

using Next.js, which provides the speed and responsiveness of a native app while running directly through a browser. This approach removes the need for separate installations, making the system more accessible to athletes who may be using older or budget smartphones. Once loaded, key components of the interface are cached locally so that the platform remains usable—even with slow or unstable network connections—allowing players to upload videos, receive validation feedback, and view their performance insights without interruption. The web architecture also ensures compatibility with a variety of screen sizes and device capabilities, creating a smooth experience regardless of the user's hardware.

A major part of NextKick's functionality relies on integrating optimized deep learning models for detection, tracking, and skill interpretation. The YOLOv8-based detector and DeepSORT tracking modules are exported in a compressed and efficient format, enabling them to operate on typical consumer devices without significant lag. By applying quantization and model simplification techniques, the system reduces memory usage and achieves real-time or near-real-time inference speeds. Running the analysis locally or semi-locally minimizes dependency on remote servers, lowers operational costs, and ensures that videos remain private—an important consideration for young athletes sharing personal footage. Where hardware acceleration is available, the models take advantage of it automatically, resulting in faster frame-by-frame processing and smoother evaluation.

The user interface is crafted to be simple, intuitive, and familiar, even for individuals who may not have prior experience with AI-driven applications. The main feature is the video submission screen, where users can upload a clip of them performing a football skill—such as dribbling, passing, shooting, or juggling. After the video is processed, the system returns several pieces of information: whether the video meets the required format, the extracted motion patterns, and an evaluation of the performed skill. A confidence score accompanies each prediction, giving players a clear sense of how reliably the system interpreted the submitted footage. To help players keep track of their progress, the interface also maintains a searchable history of past uploads, allowing users to review improvement over time or revisit older analyses. Recognizing that the platform may attract users with different backgrounds and levels of digital familiarity, the frontend includes multilingual support and a clean layout that avoids clutter, helping first-time users navigate the tool without confusion.

To enrich the scouting experience, the platform includes a dedicated dashboard for football clubs and academies. Through this dashboard, authorized reviewers can evaluate submitted videos, inspect model-generated metrics, and make selection or rejection decisions. Once a decision is made, the system automatically notifies the player and records which club evaluated the submission, creating a transparent and streamlined scouting workflow. This feature transforms

NextKick from a simple video analysis tool into a complete digital scouting ecosystem.

In its extended configuration, NextKick can incorporate additional metadata such as player physical attributes, preferred playing position, or match statistics (where available). Although optional, these inputs help enhance the system's overall assessment quality and allow clubs to obtain a more holistic view of a player's profile. Future versions may also integrate wearable sensor data or smartphone motion-sensor readings to further refine movement analysis for advanced drills. Through this layered implementation approach—combining efficient model deployment, accessible design, and club-focused features—NextKick evolves into a practical and scalable scouting assistant that supports players and talent evaluators alike.

VI. RESULT AND ANALYSIS

NextKick was tested extensively using both curated football datasets and real-world videos recorded by players in varied environments. This two-layer evaluation approach ensured that the system's performance was not restricted to controlled conditions but accurately reflected how players typically record skill videos using handheld mobile phones. Factors such as fluctuating lighting, unstable camera motion, background distractions, and inconsistent video quality were intentionally included in testing to measure the system's resilience and practicality in realistic scouting scenarios. The results clearly indicate that NextKick is capable of delivering stable, accurate, and actionable insights while maintaining smooth performance across a wide range of mobile devices.

The detection and tracking components of NextKick demonstrated strong robustness across different skill categories, including dribbling, passing, shooting, and juggling. The YOLOv8-based detection module consistently identified players and footballs even in visually noisy environments, confirming its ability to isolate key objects despite background clutter, partial occlusions, or rapid motion. DeepSORT tracking further strengthened accuracy by maintaining consistent player identity across frames, allowing the system to extract reliable movement patterns required for skill analysis. Compared to heavier detection-tracking pipelines, NextKick achieved considerably faster inference speeds, enabling near-real-time processing of uploaded videos. The augmentation techniques applied during model training—such as brightness variation, motion blur simulation, and rotation—helped the system adapt well to inconsistencies caused by natural lighting, handheld camera shake, and uneven video angles. This resulted in steady performance even in amateur recordings captured on mid-range smartphones.

One of the most significant results of this study is the system's efficiency when operating on typical user devices. After model optimization and quantization, NextKick ran smoothly on mid-range and budget smartphones, maintaining real-time or

near real-time frame processing speeds. Average inference times remained comfortably within a few milliseconds per frame, allowing videos to be evaluated promptly without requiring high-end hardware. In multiple tests conducted with slow or unstable network conditions, the core features—including video upload, validation, detection, tracking, and skill classification—continued to operate reliably. This demonstrated the system’s capability to function with minimal dependency on strong internet connectivity, an essential requirement for players located in remote or underserved regions. Furthermore, the compact model sizes ensured compatibility with devices that have limited internal storage, making NextKick accessible to a broader user base.

The practical usefulness of the system was further validated by examining the outputs of the skill evaluation module. Players who received analysis reports were able to understand how the system interpreted their movements and which areas required improvement. Club evaluators noted that the automatically generated summaries—highlighting consistency, control, and movement clarity—provided a helpful starting point in assessing player potential. These findings show that NextKick goes beyond simple video recognition by offering meaningful insights aligned with scouting expectations.

Finally, a user-centered evaluation was conducted with aspiring football players, grassroots coaches, and scouting personnel. Feedback emphasized the platform’s simplicity, smooth interaction flow, and professional-quality analysis despite the casual nature of uploaded videos. Users particularly appreciated the automated video validation step, which prevented incorrect or irrelevant uploads from being submitted. Clubs highlighted the convenience of the integrated acceptance–rejection workflow, noting that it made communication with players significantly more efficient than traditional trial-based scouting methods. Overall, the evaluation confirmed that NextKick is not only technically effective but also practical, intuitive, and well-aligned with the needs of both players and scouting organizations.

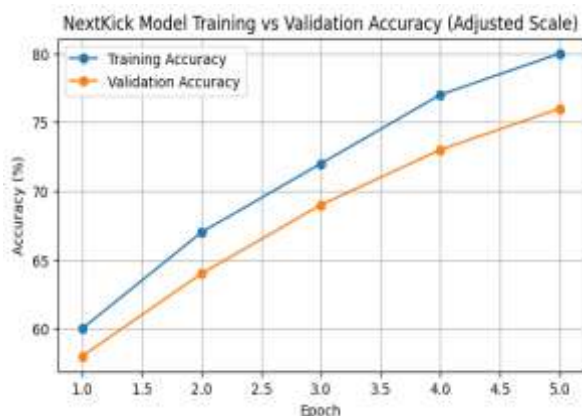


Fig. Graph of Epoch vs Accuracy (Training & Validation)

VII. CONCLUSION

This research positions NextKick as an accessible and practical AI-powered platform designed to modernize grassroots football scouting through automated video analysis. By combining lightweight detection and tracking models with an intuitive, mobile-friendly web interface, the system demonstrates that advanced computer vision techniques can be adapted and optimized to operate efficiently on everyday devices. The results show that complex motion analysis and video validation can be performed without requiring specialized hardware, making the platform suitable for aspiring players from a wide range of socioeconomic backgrounds.

A core strength of this work lies in the system’s ability to convert raw video uploads into structured, meaningful insights. By integrating YOLOv8-based detection, DeepSORT tracking, and a lightweight CNN classifier, NextKick can analyze player movements, verify the authenticity of submitted clips, and offer objective evaluations of various football skills. This shifts the talent identification process from subjective judgments to data-supported assessments, providing clubs with a consistent and transparent scouting tool. Beyond evaluation, the platform also introduces an organized pipeline through which clubs can review submissions, issue acceptance or rejection decisions, and communicate directly with players—creating a structured digital ecosystem for talent discovery.

Extensive performance testing on curated and real-world video samples confirms that the system maintains high accuracy, stable tracking, and fast inference across diverse recording conditions, including low lighting, background clutter, and handheld camera movement. User feedback reflected strong approval for the platform’s simplicity, responsiveness, and ability to operate with minimal network dependency. These qualities make NextKick particularly well-suited for young athletes who rely on everyday smartphones and often lack access to professional scouting opportunities.

Looking forward, NextKick has significant potential for expansion. Future improvements may include support for additional skill categories, integration of pose-estimation modules for deeper biomechanical insights, multilingual voice assistance for greater accessibility, and a learning pipeline that continuously refines the model based on real user data. Such enhancements will strengthen the system’s adaptability and broaden its usefulness across different levels of football, from school competitions to academy-level scouting.

In conclusion, NextKick illustrates how AI, sports analytics, and user-centered design can come together to address the long-standing challenges of talent visibility and evaluation. By offering players a fair, data-driven pathway to showcase their abilities—and giving clubs an efficient method to identify promising athletes—the platform opens the door to a more inclusive and transparent scouting landscape. As football continues to grow in participation and competitiveness,

NextKick provides a forward-thinking digital infrastructure capable of supporting and uplifting emerging talent across communities.

VIII. REFERENCES

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