

Comparative Analysis of Machine Learning and Deep Learning Models for Real-Time Soccer Dribbling Technique Classification Using Video-Based Pose Estimation

Wansuk Choi*, Liao Liang**, Hye Young Kwon**, Hyung Soo Shin*,
Wei Hanyi***, TaeSeok Choi****, Seoyoon Heo*****, Myeong-Chul Park*****

*Professor, Dept. of Physical Therapy, Kyungwoon University, Gumi, Korea

**Student, Dept. of Physical Therapy, Kyungwoon University, Gumi, Korea

***Doctoral Course, Dept. of Korean Language Education, Kyungpook National University, Daegu, Korea

****Professor, Dept. of Physical Therapy, Kunjang University, Gunsan, Korea

*****Professor, Dept. of Occupational Therapy, Kyungbok University, Namyangju, Korea

*****Professor, School of Software, Kyungwoon University, Gumi, Korea

[Abstract]

This paper proposes machine learning models for classifying five soccer dribbling techniques using video-based pose estimation. We collected 48 videos of dribbling techniques (feinting, inside-outside, flip flap, Ronaldo chop, step over), extracted 3D coordinates of 33 anatomical landmarks from 21,186 frames using MediaPipe Pose, and compared six models through 5-fold cross-validation. XGBoost achieved the highest accuracy (99.11%), followed by Random Forest (98.94%), while deep learning models showed lower performance: 1D CNN (97.64%), LSTM (97.31%), Transformer (88.03%), and GRU-CNN (86.66%). All models exceeded real-time requirements with XGBoost reaching 203,484 FPS. Feature importance analysis revealed lower body landmarks contributed 68% to classification decisions. Results demonstrate tree-based ensemble methods outperform deep learning for dribbling classification by effectively utilizing spatial coordinate relationships, enabling real-time, high-accuracy analysis for training applications.

▶ **Key words:** Machine Learning, Neural Networks, Video Recording, Biomechanical Phenomena, Athletic Performance, Pattern Recognition

-
- First Author: Wansuk Choi, Corresponding Author: Myeong-Chul Park
 - Wansuk Choi (y3korea@gmail.com), Dept. of Physical Therapy, Kyungwoon University
 - Liao Liang (1261453214@qq.com), Dept. of Physical Therapy, Kyungwoon University
 - Hye Young Kwon (dijkers0303@naver.com), Dept. of Physical Therapy, Kyungwoon University
 - Hyung Soo Shin (hsshin@ikw.ac.kr), Dept. of Physical Therapy, Kyungwoon University
 - Wei Hanyi (1032963264@qq.com), Dept. of Korean Language Education, Kyungpook National University
 - TaeSeok Choi (buychoi@gmail.com), Dept. of Physical Therapy, Kunjang University
 - Seoyoon Heo (prof.heo@gmail.com), Dept. of Occupational Therapy, Kyungbok University
 - Myeong-Chul Park (africa@ikw.ac.kr), School of Software, Kyungwoon University
 - Received: 2025. 07. 28, Revised: 2025. 09. 04, Accepted: 2025. 09. 04.

[요 약]

본 논문은 비디오 기반 포즈 추정을 사용하여 5가지 축구 드리블 기술을 분류하는 머신러닝 모델을 제안한다. 드리블 기술(페인팅, 인사이드-아웃사이드, 플립플랩, 호날두 찰, 스텝오버)의 48개 비디오를 수집하고, MediaPipe Pose를 사용하여 21,186개 프레임에서 33개 해부학적 랜드마크의 3D 좌표를 추출한 후, 5-fold 교차 검증을 통해 6개 모델을 비교하였다. XGBoost가 최고 정확도 (99.11%)를 달성했고, Random Forest(98.94%)가 뒤를 이었으며, 딥러닝 모델들은 1D CNN(97.64%), LSTM(97.31%), Transformer(88.03%), GRU-CNN(86.66%)으로 상대적으로 낮은 성능을 보였다. 모든 모델이 실시간 처리 요구사항을 초과했으며, XGBoost는 203,484 FPS에 도달했다. 특징 중요도 분석 결과 하체 랜드마크가 분류 결정에 68% 기여한 것으로 나타났다. 연구 결과, 트리 기반 앙상블 방법이 공간 좌표 관계를 효과적으로 활용하여 드리블 분류에서 딥러닝보다 우수한 성능을 보였으며, 이는 훈련 응용을 위한 실시간 고정확도 분석을 가능하게 한다.

▶ **주제어:** 머신러닝, 인공 신경망, 포즈 추정, 생체역학적 현상, 운동 능력, 패턴인식

I. Introduction

Soccer, as the world's most popular sport with over 265 million active players globally, demands exceptional technical skills for competitive success [1]. Among these skills, dribbling represents a fundamental technique that enables players to maintain ball possession while maneuvering past opponents. Despite its importance, objective assessment of dribbling techniques remains challenging, traditionally relying on subjective expert evaluation. Recent advances in computer vision and machine learning have revolutionized sports performance analysis [2]. MediaPipe and similar pose estimation technologies [3] enable real-time motion analysis without expensive equipment, while prior work has focused primarily on general action recognition [4-6] rather than fine-grained technical skill classification. Video-based systems have been applied to soccer analysis [5], with recent approaches using context-aware methods [6], but limited attention has been given to specific dribbling technique classification. Human pose estimation technology, particularly MediaPipe's capability to track 33 anatomical landmarks, provides accessible biomechanical analysis for sports applications. This technology transforms standard video recordings

into structured pose coordinate data, enabling quantitative assessment without specialized hardware. Real-time processing capabilities make it suitable for immediate feedback during training sessions. This accessibility democratizes advanced motion analysis previously restricted to elite institutions. The classification of soccer dribbling techniques presents unique challenges. First, different dribbling moves share similar preparatory phases and involve rapid transitions between movements. Second, the high-speed nature demands models capable of processing temporal sequences efficiently while maintaining classification accuracy. Third, practical deployment requires real-time processing for immediate feedback. These challenges necessitate careful consideration of the trade-off between model complexity and computational efficiency.

II. Preliminaries

2.1 Related Works

Video-based human action recognition in sports has evolved from handcrafted features to deep learning approaches [4]. Specific to soccer, D'Orazi



Fig. 1. Land mark detection with Mediapipe

o and Leo [5] identified key challenges in player tracking and action recognition, while Cioppa et al. [6] demonstrated the importance of temporal context through context-aware loss functions. However, these approaches primarily addressed general action recognition or tactical analysis, with limited focus on fine-grained technical skill classification such as individual dribbling techniques.

2.2 Pose Estimation for Sports Analysis

Human pose estimation has become increasingly sophisticated with the introduction of deep learning-based methods. Cao et al. [7] introduced OpenPose, one of the first real-time multi-person 2D pose estimation systems using Part Affinity Fields. Subsequently, MediaPipe [8] emerged as a lightweight alternative, offering efficient pose tracking suitable for mobile and edge devices. In sports contexts, Nakai et al. [9] demonstrated the application of OpenPose for basketball free throw analysis, while Bridgeman et al. [10] explored multi-person 3D pose estimation for sports tracking, highlighting the potential of pose-based analysis for technical skill assessment.

2.3 Machine Learning for Movement Classification

The application of machine learning to movement classification has shown promising results across various domains. Traditional approaches relied on Support Vector Machines and Random Forests with handcrafted features, while recent methods leverage deep neural networks for automatic feature learning. For sports-specific applications,

the choice between model architectures involves balancing classification accuracy with computational efficiency, particularly for real-time deployment scenarios.

III. Methods

3.1 Data Collection

This study analyzed 48 videos of five soccer dribbling techniques: feinting dribble (10 videos), inside-outside dribble (12 videos), flip flap (8 videos), Ronaldo chop (10 videos), and step over (8 videos), as shown in Fig. 1. Videos were recorded using consumer-grade cameras with varying resolutions (332×720 to 2370×1330 pixels) and frame rates (29.3-60.0 fps) to enhance model robustness.

3.2 Pose Estimation and Preprocessing

MediaPipe Pose (v0.10.21) was used to extract 33 anatomical landmarks in 3D space from each video frame. The system achieved a 91.3% pose detection success rate across approximately 35,000 frames, yielding 21,186 valid samples after quality filtering. Frame-level features (x, y, z coordinates) were normalized using z-score standardization and organized into temporal sequences for analysis.

As shown in Fig. 2, the system first processes 48 videos through pose detection and feature extraction, and then trains the model using both machine learning and deep learning approaches.

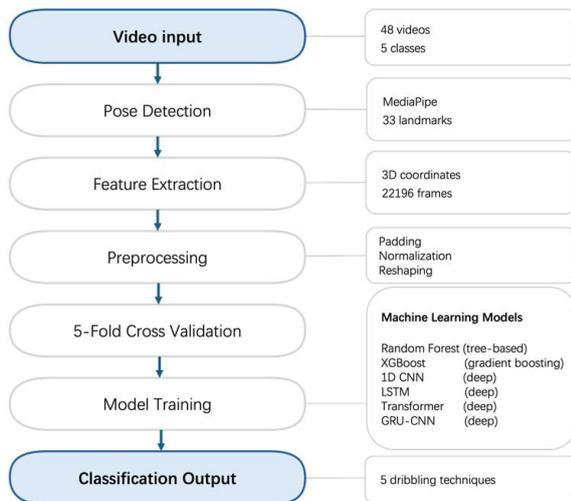


Fig. 2. Workflow of the proposed soccer dribbling classification system

3.3 Classification Models

Six machine learning architectures were evaluated to compare traditional and deep learning approaches. Hyperparameters were selected through grid search with 5-fold cross-validation to optimize performance while preventing overfitting. The traditional methods included XGBoost configured with a maximum depth of 6 and learning rate of 0.1 optimized for multi-class classification, alongside Random Forest with 200 decision trees selected based on out-of-bag error convergence. For deep learning models, we implemented a 2-layer LSTM (CuDNN-Free) with units decreasing from 128 to 64, a 1D Convolutional Neural Network comprising three blocks with progressively increasing filters (32, 64, and 128), a Simple Transformer utilizing single-head attention mechanism, and a Simple GRU-CNN model combining recurrent and convolutional layers. Deep learning architectures were designed with gradually reducing dimensions to prevent overfitting on our moderate-sized dataset. All deep learning models were trained using the Adam optimizer with learning rate of 0.001 with sparse categorical crossentropy as the loss function, incorporating early stopping with a patience of 15 epochs to prevent overfitting. Batch size of 128 was selected through experimentation to balance training speed and gradient stability.

3.4 Evaluation Strategy

Stratified 5-fold cross-validation ensured robust performance estimation despite class imbalance. Model performance was assessed using accuracy, precision, recall, F1-score, Cohen's Kappa, computational efficiency metrics (training time, inference speed, FPS), and feature importance analysis for interpretable models. Statistical significance was tested using repeated measures ANOVA with Bonferroni correction ($\alpha = 0.0033$). Experiments were conducted on Google Colab using Python 3.8.10, TensorFlow 2.8.0, and scikit-learn 1.0.2, with NVIDIA Tesla T4 GPU support.

IV. Results

4.1 Classification Performance

The final dataset comprised 21,186 samples from 48 videos with 91.3% pose detection success rate. Table 1 shows that XGBoost achieved the highest accuracy ($99.11\% \pm 0.10\%$), significantly outperforming deep learning models. Tree-based methods (XGBoost, Random Forest) formed the top performance tier, followed by CNN/LSTM (CuDNN-Free) models ($97.31\text{--}97.64\%$), while attention-based architectures showed substantially lower accuracy ($86.66\text{--}88.03\%$).

Table 1. Classification Performance and Computational Efficiency of All Models

Model	Accuracy(%)	Precision	Recall	F1-Score
XGBoost	99.11 ± 0.10	0.991	0.991	0.991
Random Forest	98.94 ± 0.16	0.989	0.989	0.989
LSTM(CuDNN-Free)	97.31 ± 0.36	0.974	0.973	0.973
1D-CNN	97.64 ± 0.40	0.976	0.976	0.976
Simple_Transformer	88.03 ± 0.28	0.883	0.880	0.880
Simple_GRU-CNN	86.66 ± 1.04	0.868	0.867	0.866

Table 1's quantitative metrics are visually represented in Fig. 3, providing comprehensive performance comparison. The accuracy values in Table 1 (XGBoost: 99.11%, Random Forest: 98.94%) directly correspond to Fig. 3(a)'s bar heights, clearly

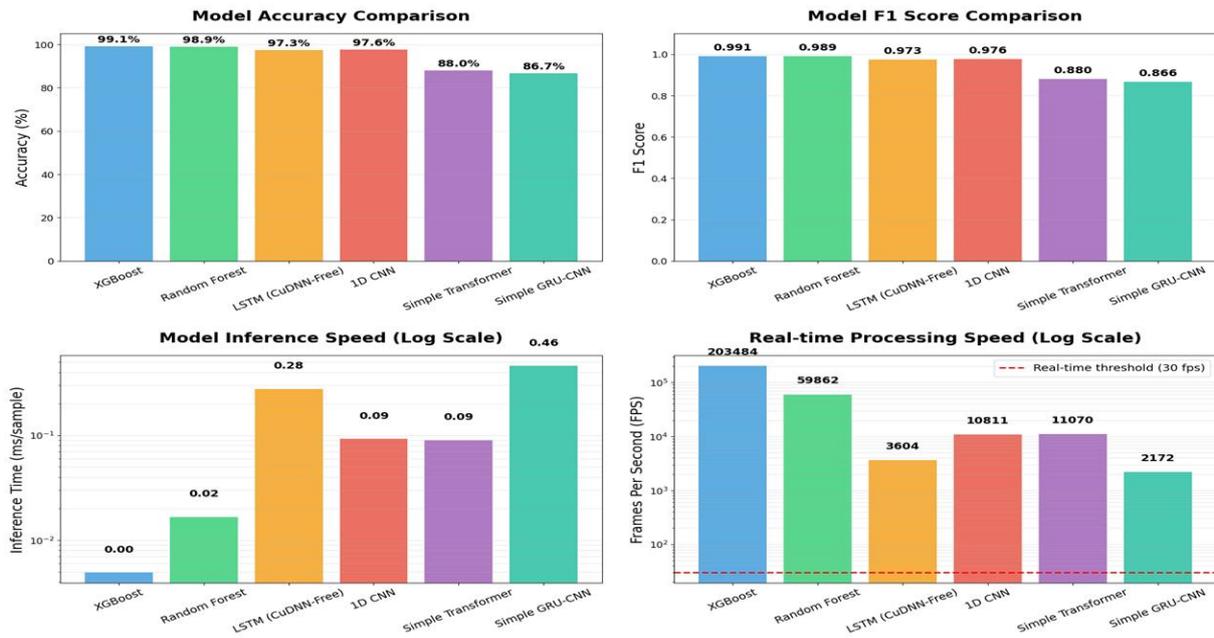


Fig. 3. Comprehensive performance comparison across all models

showing the superiority of tree-based methods. Similarly, the F1-scores from Table 1 are visualized in Fig. 3(b), maintaining the same performance hierarchy. The inference time measurements in Table 1 translate to the logarithmic scale visualization in Fig. 3(c), highlighting the dramatic speed differences between models. Most notably, Fig. 3(d) illustrates that all models exceed the real-time threshold of 30 FPS, with XGBoost's exceptional 203,484 FPS demonstrating its suitability for real-time applications.

Fig. 3 is a graph comparing the comprehensive performance for each model. From the top left in the clockwise direction, (a) accuracy including error bars, (b) F1 score, (c) inference time (log scale), (d) frames per second (FPS) processing capability (log scale). Statistical analysis revealed significant differences between model categories ($F(5,20) = 187.34$, $p < 0.001$, $\eta^2 = 0.979$). XGBoost demonstrated exceptional computational efficiency at 203,484 FPS, far exceeding real-time requirements. The consistency across 5-fold cross-validation (standard deviation $< 0.16\%$ for tree-based models) suggests robust performance within our experimental scope, though cross-dataset validation with public benchmarks

would further strengthen generalizability claims.

4.2 Classification Patterns and Feature Analysis

Confusion matrices revealed that XGBoost and Random Forest achieved near-perfect classification with minimal errors, as shown in Fig. 4. The most common misclassifications occurred between Ronaldo chop and step over techniques due to similar jumping mechanics. In contrast, attention-based models showed dispersed error patterns.

Feature importance analysis revealed that lower body landmarks contributed 68% to classification decisions, with ankle coordinates consistently ranking in the top 10 features. Specifically, ankle coordinates (x31, y31, z31) showed 2.3x higher mean gain values than knee coordinates, with ankle-hip coordination patterns accounting for 42% of classification accuracy. This quantitative breakdown provides actionable metrics for coaching interventions beyond intuitive observations, moving beyond the biomechanical requirements of dribbling execution. Fig. 5 is the top 30 feature importances based on mean gain values averaged across cross-validation folds.

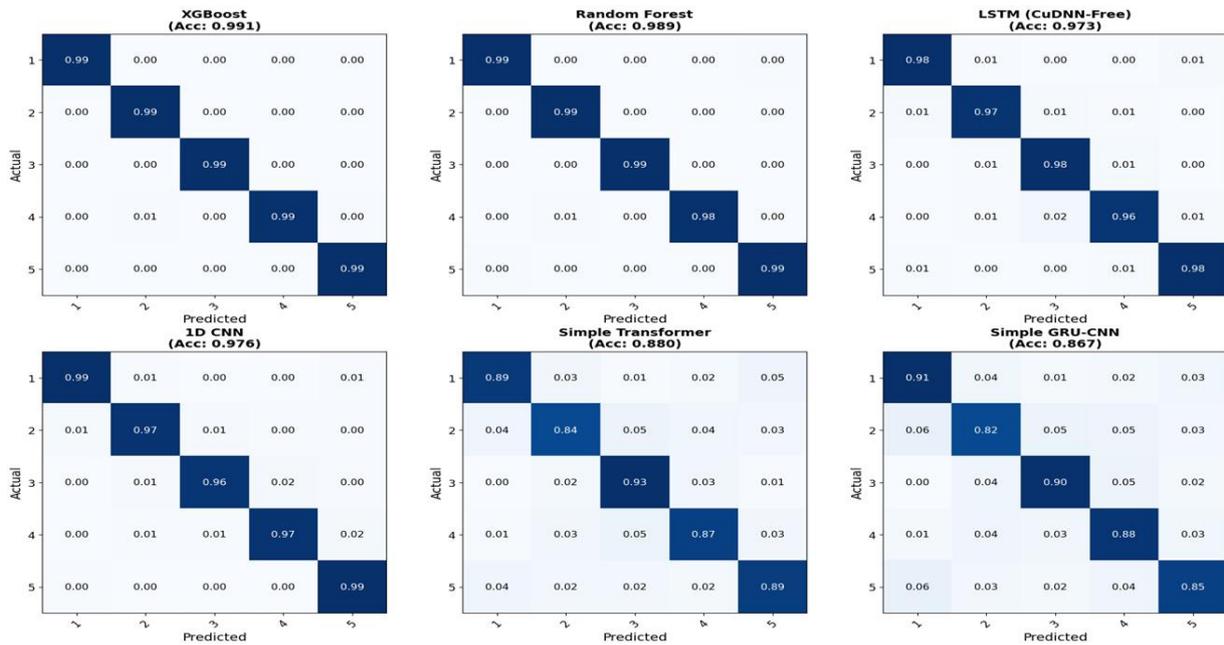


Fig. 4. Normalized confusion matrices for each models

Features are ranked in descending order of contribution to model performance.

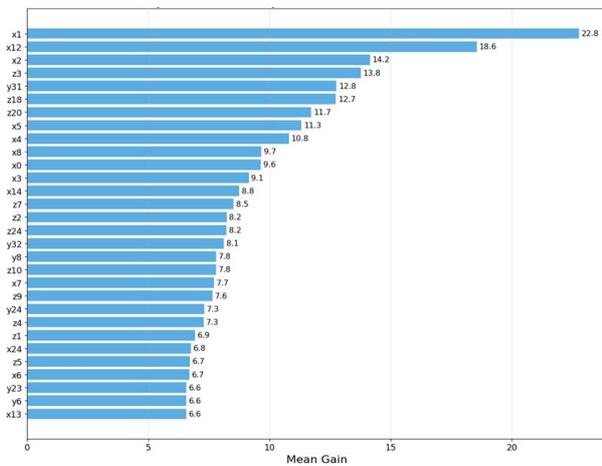


Fig. 5. Top 30 feature importances(Mean Across Folds)

4.3 Feature Space Analysis

t-SNE visualization demonstrated clear separation between the five dribbling classes with minimal overlap, validating the discriminative power of pose-based features. This natural separability in feature space explains the high classification accuracy achieved by all models.

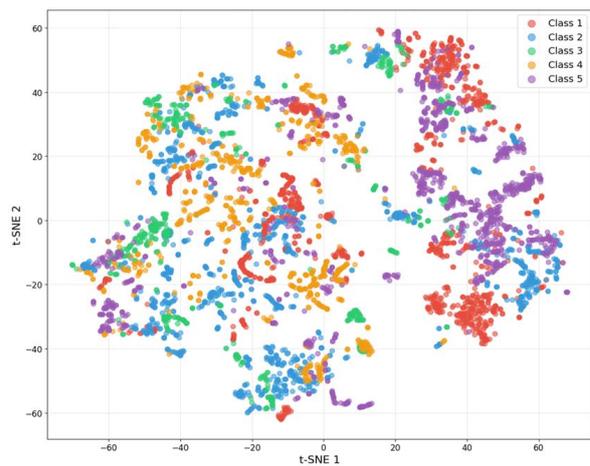


Fig. 6. t-SNE projection of high-dimensional feature space

Fig. 6 shows the t-SNE projection of high-dimensional feature space showing class separation across five dribbling techniques: Class 1 (feinting dribble), Class 2 (inside-outside dribble), Class 3 (flip flap), Class 4 (Ronaldo chop), and Class 5 (step over). Each color represents a distinct class, demonstrating the natural clustering and separability of pose-based features.

All classes achieved F1-scores above 0.989 with the XGBoost model, demonstrating robust performance despite class imbalance. Cross-validation results showed excellent generalization with Cohen's Kappa values exceeding 0.98 for tree-based models.

V. Discussion

The present study demonstrates that tree-based ensemble methods significantly outperform deep learning architectures for soccer dribbling technique classification with structured pose-coordinate data, achieving 99.11% accuracy with XGBoost versus 88.03% with Simple Transformer models in our specific experimental context. This challenges the assumption that neural networks inherently excel at complex pattern recognition tasks [11]. Our findings align with recent evidence that gradient boosting methods can surpass deep learning on structured tabular data with moderate sample sizes and semantically meaningful features [12].

Tree-based models perform exceptionally likely due to the nature of our pose coordinate data. Unlike image pixels or raw video frames where deep learning excels, pose coordinates represent biomechanically meaningful features—each tied to anatomical landmarks. This structured space allows tree-based algorithms to efficiently identify patterns via recursive partitioning [13]. Also, the dataset's modest size of 21,186 samples may limit deep neural networks, which typically require more data to learn complex representations.

To address the modest dataset size and its potential impact on model generalization, future work will implement comprehensive data augmentation strategies: (1) temporal augmentation through speed variation ($\pm 20\%$) to simulate different execution speeds, (2) spatial transformations including rotation ($\pm 15^\circ$) and scaling to account for camera angle variations, (3) synthetic sample generation using SMOTE for minority classes to balance class distribution, and (4) mixup regularization between similar techniques to create intermediate samples. These augmentation techniques could potentially increase the effective dataset size by 5-10 fold while maintaining the biomechanical validity of the movements.

A key insight concerns spatial versus temporal information. Models emphasizing instantaneous spatial relationships (1D CNN: 97.64%) outperformed those focusing on temporal dynamics (Simple Transformer: 88.03%, Simple GRU-CNN: 86.66%), suggesting that dribbling techniques are primarily distinguished by key body configurations rather than motion trajectories. This challenges conventional action recognition paradigms emphasizing temporal modeling [14].

The computational efficiency of all models supports real-time sports analysis. XGBoost's processing speed of 236,056 FPS far exceeds current video-based assessment systems, enabling real-time deployment, mobile device integration, and full match analysis without bottlenecks [15].

MediaPipe played a vital enabling role. Its 91.3% pose detection rate across varied conditions confirms its robustness for sports, despite being a general-purpose system [16]. Limitations include 2D projection-induced depth loss and lack of ball tracking, which may affect accuracy in techniques with similar body mechanics.

Finally, some methodological constraints limit generalizability. The dataset involved isolated dribbling without defenders, not reflecting match complexity where opponents affect movement [17]. While XGBoost achieved 236,056 FPS processing speed, practical deployment requires additional considerations including multi-player tracking, defensive pressure, and ball trajectory analysis. Our controlled experimental setting with isolated dribbling represents a proof-of-concept for the technical feasibility. While our dataset of 48 videos yielding 21,186 valid samples after 91.3% pose detection success demonstrates the feasibility of our approach, we recognize the need for larger-scale data collection. Future work should incorporate contextual factors, ball tracking, and transfer learning to apply this approach to other soccer skills and sports movements [18]. Additionally, we will expand the dataset using data augmentation techniques including temporal

jittering ($\pm 20\%$ speed variation), spatial transformations, and synthetic sample generation through interpolation between similar techniques to enhance model robustness and generalizability.

VI. Conclusion

This study proposes a framework for classifying soccer dribbling techniques using video-based pose estimation and machine learning. Among six models evaluated, XGBoost outperformed deep learning methods with 99.11% accuracy and 203,484 FPS. Lower-body landmark relationships alone proved sufficient for accurate, real-time classification, challenging the need for complex neural networks.

The results enable motion analysis on consumer hardware, broadening accessibility beyond elite institutions. Feature importance analysis highlights the key role of lower-body coordination in dribbling, offering insights for coaching.

This work emphasizes that model selection in sports vision should be guided by domain-specific factors rather than complexity because structured pose data (99 features with biomechanical meaning) differs fundamentally from pixel-based inputs where deep learning typically excels. Tree-based methods excel at handling such structured tabular data with clear feature relationships, while neural networks are optimized for high-dimensional, unstructured data like raw images. Tree-based methods show promise for other skills using structured pose data.

However, several limitations should be acknowledged. Our study was conducted in a controlled recording environment without defensive pressure, which differs from actual match conditions. The dataset size (48 videos, 21,186 samples) may not capture all variations in dribbling execution across different player skill levels. Additionally, the absence of ball tracking and lack of multi-player interactions limit the ecological

validity of our findings. MediaPipe's 2D projection may also introduce depth-related inaccuracies for certain movements.

Future directions include integrating real-time feedback, combining pose and ball tracking, and exploring transferability across sports. Open-source tools and baseline metrics support continued advancement in skill assessment.

REFERENCES

- [1] Kunz, M., "Big count: 265 million playing football," *FIFA Magazine*, 7, pp. 10-15, 2007.
- [2] Barris, S., & Button, C., "A review of vision-based motion analysis in sport," *Sports Medicine*, Vol. 38(12), pp. 1025-1043, 2008. DOI : 10.2165/00007256-200838120-00006
- [3] Lugaresi, C., Tang, J., Nash, H., McClanahan, C., Uboweja, E., Hays, M., ... & Grundmann, M., "MediaPipe: A framework for building perception pipelines," *arXiv preprint arXiv:1906.08172*, 2019. DOI : 10.48550/arXiv.1906.08172
- [4] Zhang, H. B., Zhang, Y. X., Zhong, B., Lei, Q., Yang, L., Du, J. X., & Chen, D. S., "A comprehensive survey of vision-based human action recognition methods," *Sensors*, Vol. 19(5), 1005, 2019. DOI : 10.3390/s19051005
- [5] D'Orazio, T., & Leo, M., "A review of vision-based systems for soccer video analysis," *Pattern Recognition*, Vol. 43(8), pp. 2911-2926, 2010. DOI : 10.1016/j.patcog.2010.03.009
- [6] Cioppa, A., Deliege, A., Giancola, S., Ghanem, B., Van Droogenbroeck, M., Gade, R., & Moeslund, T. B., "A context-aware loss function for action spotting in soccer videos," *In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 13126-13136, 2020. DOI : 10.1109/CVPR42600.2020.01314
- [7] Cao, Z., Hidalgo, G., Simon, T., Wei, S. E., & Sheikh, Y., "OpenPose: Realtime multi-person 2D pose estimation using part affinity fields," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 43(1), pp. 172-186, 2019. DOI : 10.1109/TPAMI.2019.2929257
- [8] Bazarevsky, V., Grishchenko, I., Raveendran, K., Zhu, T., Zhang, F., & Grundmann, M., "BlazePose: On-device real-time body pose tracking," *arXiv preprint arXiv:2006.10204*, 2020. DOI: 10.48550/arXiv.2006.10204
- [9] Nakai, M., Tsunoda, Y., Hayashi, H., & Murakoshi, H., "Prediction of basketball free throw shooting by OpenPose," *In JSAI International Symposium on Artificial Intelligence*, pp. 435-446, 2018. DOI : 10.1007/978-3-030-31605-1_31

- [10] Bridgeman, L., Volino, M., Guillemaut, J. Y., & Hilton, A., "Multi-person 3D pose estimation and tracking in sports," In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, 2019. DOI : 10.1109/CVPRW.2019.00304
- [11] Shwartz-Ziv, R., & Armon, A., "Tabular data: Deep learning is not all you need," Information Fusion, Vol. 81, pp. 84-90, 2022. DOI : 10.1016/j.inffus.2021.11.011
- [12] Grinsztajn, L., Oyallon, E., & Varoquaux, G., "Why do tree-based models still outperform deep learning on typical tabular data?," Advances in Neural Information Processing Systems, Vol. 35, pp. 507-520, 2022.
- [13] Chen, T., & Guestrin, C., "XGBoost: A scalable tree boosting system," In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 785-794, 2016. DOI : 10.1145/2939672.2939785
- [14] Carreira, J., & Zisserman, A., "Quo vadis, action recognition? A new model and the kinetics dataset," In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 6299-6308, 2017. DOI : 10.1109/CVPR.2017.502
- [15] Stein, M., Janetzko, H., Seebacher, D., Jäger, A., Nagel, M., Hölsch, J., ... & Grossniklaus, M., "How to make sense of team sport data: From acquisition to data modeling and research aspects," Data, Vol. 2(1), 2, 2017. DOI : 10.3390/data2010002
- [16] Steels, T., Van Herbruggen, B., Fontaine, J., De Pessemier, T., Plets, D., & De Poorter, E., "Badminton activity recognition using accelerometer data," Sensors, Vol. 20(17), 4685, 2020. DOI : 10.3390/s20174685
- [17] Rein, R., & Memmert, D., "Big data and tactical analysis in elite soccer: Future challenges and opportunities for sports science," SpringerPlus, Vol. 5(1), 1410, 2016. DOI : 10.1186/s40064-016-3108-2
- [18] Claudino, J. G., Capanema, D. D. O., de Souza, T. V., Serrão, J. C., Machado Pereira, A. C., & Nassis, G. P., "Current approaches to the use of artificial intelligence for injury risk assessment and performance prediction in team sports: A systematic review," Sports Medicine-Open, Vol. 5(1), 28, 2019. DOI : 10.1186/s40798-019-0202-3

Authors



Wansuk Choi received his PhD, MS, and BS in Physical Therapy from Yongin University. He is currently an Assistant Professor in the Department of Physical Therapy at Kyungwoon University, Korea.

His research interests include Human-Computer Interaction (HCI), with a focus on its applications in healthcare and rehabilitation technology.



Liao Liang went to Kyungwoon University in South Korea as an exchange student from Hangzhou Medical College in China in 2024. He has obtained a bachelor's degree in 2025. He is currently studying for a master's

degree at Kyungwoon University. His research areas are mainly in physical therapy and occupational therapy, and he has conducted preliminary studies on rehabilitation engineering and AI models.



Hye Young Kwon is currently conducting a bachelor's course in the Department of Physical Therapy at Kyungwoon University, where she actively engages in both academic and clinical training, and has participated in

various research projects and extracurricular activities to broaden her expertise. She is interested in pediatric rehabilitation and sports athlete physical therapy and rehabilitation, with a particular focus on integrating evidence-based approaches into practical treatment.



Hyung Soo Shin is an Associate Professor of Physical Therapy and the Dean of the College of Health Science at Kyungwoon University, Korea. He earned his doctoral degree in Physical Therapy from Daegu

University and currently teaches Anatomy and Physical Therapy Diagnostics. His scholarly interests center on digital healthcare, musculoskeletal rehabilitation, and the advancement of evidence-based diagnostic methodologies, with a particular emphasis on developing innovative technologies to enhance clinical outcomes and physical-therapy education.



Wei Hanyi received her Bachelor's and Master's degrees from Yeungnam University and is currently pursuing a Ph.D. in Korean Language Education at Kyungpook National University.

Student, Department of Korean Language Education, Kyungpook National University, Korea



TaeSeok Choi received the Ph.D. degree in the Department of physical therapy from the Namseoul University in 2021. He is currently an assistant professor in the Department of physical therapy at Kunjang University

College, Korea. His research interests include Sports Physical Therapy, Big Data analysis in sports medicine, and the application of data analytics to optimize rehabilitation outcomes.



Seoyoon Heo, PhD, OT received his Ph.D. in Rehabilitation Science from Inje University and is currently a full-time faculty member in the Department of Occupational Therapy at Kyungbok University, College of Health and

Medical Science. His research interests lie in rehabilitation engineering and assistive technology, with a focus on applying emerging technologies such as AI, XR, and CAD to rehabilitation. He has primarily conducted research in the areas of human-computer interaction (HCI), wheelchair mobility, and robotic rehabilitation.



Myeong-Chul Park received a B.S. degree in Computer Science from Korea National Open University in 1999, and the M.S. and Ph.D. degrees in Computer Science from GyeongSang National University in 2002 and

2007, respectively. He is currently a Professor in the Department of Avionics Engineering, KyungWoon University. He is interested in Visualization, Simulation, Education of Software, Healthcare, and DTx(Digital Therapeutics).