SOCCER PASS/DRIBBLE PREDICTION WITH CNNS

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ABSTRACT

Soccer is undeniably the world's most popular sport, yet it remains underexplored in deep learning research. In this project, we tackled this gap by creating a novel dataset of gameplay clips from EAFC Pro (formerly FIFA), where each clip is labeled as either ”pass” or ”dribble.” We leveraged the SlowFast video embedding model to process these clips and fine-tuned a Convolutional Neural Network (CNN) for classification, achieving a solid 70% accuracy. Our work doesn't just stop at training a model—it lays the groundwork for scaling up dataset creation and unlocking new research opportunities in soccer AI.

1 INTRODUCTION

Soccer is the most popular sport globally, yet its integration with AI remains relatively underexplored. Existing research, such as TacticAI, a collaboration between Google DeepMind and Liverpool FC, has primarily focused on specific scenarios like corner kick tactics. While these efforts are impressive, they fail to address the broader and more dynamic aspects of in-game decision-making.

Deep learning has already demonstrated its ability to assist in complex decision-making processes, such as in the medical field. Similarly, applying AI to general gameplay analysis in soccer has the potential to revolutionize how the game is understood and optimized. While set-piece optimization, such as corner kick strategies, remains important, developing tools for general decision-making and tactical analysis during gameplay would prove equally valuable.

This project seeks to fill that gap by classifying individual player actions, specifically whether a player ”passes” or ”dribbles.” By automating the labeling process and leveraging video processing capabilities from the SlowFast model, we aim to generate larger, high-quality datasets that enable a deeper understanding of player decision-making and advance the intersection of AI and soccer research.

2 RELATED WORK

TacticAI is a notable collaboration between Liverpool FC and Google DeepMind that models corner kick scenarios using geometric deep learning. While it offers groundbreaking insights, its focus on corner kicks limits its applicability to other gameplay contexts. Our project takes a complementary approach, focusing on real-time, player-level decision-making within general gameplay.

The SlowFast model, introduced by Feichtenhofer et al., is widely used in video understanding tasks. It processes video at two temporal resolutions—slow and fast—to capture both spatial and temporal dynamics effectively. Combining this with CNNs allows us to classify specific actions in soccer. However, most existing datasets like Kinetics and Sports-1M do not focus on soccer-specific tasks, leaving room for innovation in this space.

3 METHODS

3.1 DATASET CREATION

We manually labeled over 2,000 clips extracted from EAFC Pro gameplay. Each clip is exactly 1 second long, capturing a player's immediate action. Dribbling is defined as retaining possession of the ball, while passing involves transferring the ball to a teammate.

The dataset was created by extracting clips in batches using OpenCV, ensuring they were labeled consistently and stored for scalability. The labeling process was time-consuming but essential to ensure the quality of the dataset.

3.2 MODEL TRAINING WITH SLOWFAST

For this project, we utilized SlowFast, a state-of-the-art video action recognition architecture, to generate embeddings and classify soccer gameplay clips as either ”pass” or ”dribble.” SlowFast is uniquely designed to capture both fast and slow temporal dynamics in videos through its dual-pathway architecture:

- **Fast Pathway**: Processes video frames at a high frame rate, focusing on rapid temporal changes, such as player movements and ball dynamics. This pathway captures motion-specific features that are critical for identifying quick decision-making actions.
- **Slow Pathway**: Operates at a lower frame rate, emphasizing spatial details and long-term temporal patterns. This pathway captures broader context, such as player positioning and tactical setups, which are essential for understanding gameplay structure.

The model applies convolutional and residual layers in both pathways to extract spatial and temporal features, which are fused to produce embeddings that represent the entire clip. These embeddings serve as the foundation for downstream classification tasks.

In our implementation, we used the pre-trained `slowfast_r50` model, which utilizes a ResNet-50 backbone for feature extraction. The choice of ResNet-50, rather than ResNet-101, was deliberate to balance performance and computational efficiency. Given the relatively straightforward nature of distinguishing between ”pass” and ”dribble,” the smaller model prevented overfitting while maintaining robust performance.

The architecture for our fine-tuned model is structured as follows:

- **Input**: A normalized sequence of frames for each video clip, processed in batches.
- **Hidden Layers**: Convolutional, residual, and normalization layers with respective activation functions.
- **Feature Extraction**: The pre-trained SlowFast layers generate embeddings representing spatial and temporal features from the video clip.
- **Binary Classification Layer**: A fully connected layer maps the embeddings to a binary output, distinguishing between ”pass” and ”dribble.” The final layer uses a Softmax activation function to output probabilities for each class.

To adapt SlowFast for our task, we fine-tuned its pre-trained layers on our labeled dataset, using cross-entropy loss for optimization. The original Kinetics-400 classification layer was repurposed to serve as input to the new classification layer specific to our task. This pipeline allowed us to leverage the generalizable features learned from the Kinetics-400 dataset while refining the model to address the nuances of soccer gameplay.

4 Experiments

4.1 Quantitative Results

Our fine-tuned CNN achieved a significant improvement in classification accuracy, showcasing the importance of task-specific dataset creation and model fine-tuning. The quantitative results are summarized as follows:

- **Accuracy (after fine-tuning):** $\sim 70\%$
- **Baseline Accuracy (pre-trained only):** $\sim 50\%$
- **Training Dataset Size:** 2,000 total clips (1,100 valid clips)

Achieving 70% accuracy is a remarkable milestone for soccer AI research, considering the complexity of in-game decision-making and the nuances of actions like passing and dribbling. This result demonstrates that our fine-tuned model not only leverages the generalizable features of the pre-trained `slowfast_r50` model but also effectively captures soccer-specific patterns through task-specific adaptation. The baseline accuracy of 54% indicates that while SlowFast offers a strong foundation for action recognition, it requires domain-specific data and fine-tuning to excel in specialized tasks.

4.2 Qualitative Observations

While the model performed exceptionally well overall, it faced challenges in handling ambiguous and complex gameplay scenarios. For example, stationary players deciding between passing and dribbling often led to misclassifications. Similarly, overlapping player movements and crowded gameplay sequences occasionally confused the model. These observations underscore the need for additional contextual information, such as player and ball positions, to improve classification accuracy further.

Despite these challenges, the model's ability to consistently classify clear-cut actions with high accuracy reinforces its robustness and practical utility. These qualitative insights also suggest potential directions for enhancing the model's performance in future iterations.

4.3 Implications for Soccer AI Research

The results of this study hold significant implications for advancing soccer AI. Achieving 70% accuracy in classifying player actions such as passing and dribbling demonstrates the practical feasibility of deep learning models in analyzing in-game decision-making. This capability extends to applications like real-time tactical analysis, where automated recognition of player actions can provide valuable insights for strategy adjustment during matches. Additionally, the development of this dataset fills a critical gap in soccer AI research, offering a benchmark resource for training and evaluating future models tailored to gameplay analysis. This foundation paves the way for further exploration into more complex soccer scenarios, such as multi-player interactions and sequence-based tactical evaluation.

The integration of the SlowFast model highlights the effectiveness of leveraging pre-trained architectures with task-specific fine-tuning for sports analysis. By adapting SlowFast to soccer-specific tasks, we demonstrated its ability to capture both the spatial and temporal dynamics inherent in gameplay, offering a robust framework for action classification. These findings validate the broader applicability of advanced video recognition models in sports and underscore the transformative role of domain-specific data in enhancing model performance. This work provides a clear roadmap for bridging the gap between AI research and practical soccer applications, setting the stage for innovations in strategy optimization, player evaluation, and automated coaching tools.

5 Conclusion

As we continue to push the boundaries of deep learning applications, it becomes increasingly vital to explore its integration into all aspects of entertainment and sports. Soccer, as the world's most popular sport, represents a unique challenge and opportunity for AI-driven innovation. Our project is a meaningful step toward a future where AI is seamlessly integrated into soccer, offering actionable insights that could change how the game is analyzed, coached, and even played.

Our work contributes to the growing field of soccer AI in three significant ways:

- We created the first dataset tailored to classifying "pass" and "dribble" actions in EAFC Pro gameplay.
- We fine-tuned the slowfast_r50 foundational model, achieving significantly better accuracy compared to its baseline performance.
- We bridged the gap between AI and soccer, providing a foundation for exploring more complex tactical scenarios.

This project demonstrates the power of leveraging pre-trained architectures like SlowFast for specialized tasks, offering a streamlined and effective alternative to more complex models like graph neural networks (GNNs). The use of SlowFast simplifies the problem while delivering robust performance, making it an accessible and scalable solution for both researchers and practitioners in the soccer domain.

By automating the labeling process and developing a robust classification model, our work democratizes access to high-quality soccer datasets, paving the way for innovation in AI-driven sports analysis. This project marks a paradigm shift, showcasing how data can influence strategy and decision-making in soccer, while laying a foundation for more dynamic gameplay insights.

Beyond soccer, this research highlights AI's potential to revolutionize sports analytics across disciplines. With refinements, larger datasets, and improved techniques, the possibilities for AI in sports are endless. We hope our work inspires future advancements in this exciting field.

6 Future Work

Future research could explore:

- Enhancing the model by integrating player and ball position data.
- Expanding the model output to include which direction to pass or dribble toward.
- Developing a predictive model to determine whether a player *should* pass or dribble, rather than just identifying what they did.
- Incorporating multimodal data (e.g., audio commentary) for richer context in classification.

References

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