SoccerNet-Echoes: A Soccer Game Audio Commentary Dataset

Sushant Gautam[1,2]   **Mehdi Houshmand Sarkhoosh**[2,3]   **Jan Held**[5]   **Cise Midoglu**[1,3]
Anthony Cioppa[5,6]   **Silvio Giancola**[6]   **Vajira Thambawita**[1]
Michael A. Riegler[1]   **Pål Halvorsen**[1,2,3]   **Mubarak Shah**[4]
[1]*SimulaMet, Norway*   [2]*OsloMet, Norway*   [3]*Forzasys, Norway*
[4]*University of Central Florida, USA*   [5]*University of Liège, Belgium*   [6]*KAUST, Saudi Arabia*
https://github.com/SoccerNet/sn-echoes

Abstract

The application of Automatic Speech Recognition (ASR) technology in soccer offers numerous opportunities for sports analytics. Specifically, extracting audio commentaries with ASR provides valuable insights into the events of the game, and opens the door to several downstream applications such as automatic highlight generation. This paper presents SoccerNet-Echoes, an augmentation of the SoccerNet dataset with automatically generated transcriptions of audio commentaries from soccer game broadcasts, enhancing video content with rich layers of textual information derived from the game audio using ASR. These textual commentaries, generated using the *Whisper* model and translated with *Google Translate*, extend the usefulness of the SoccerNet dataset in diverse applications such as enhanced action spotting, automatic caption generation, and game summarization. By incorporating textual data alongside visual and auditory content, SoccerNet-Echoes aims to serve as a comprehensive resource for the development of algorithms specialized in capturing the dynamics of soccer games. We detail the methods involved in the curation of this dataset and the integration of ASR. We also highlight the implications of a multimodal approach in sports analytics, and how the enriched dataset can support diverse applications, thus broadening the scope of research and development in the field of sports analytics.
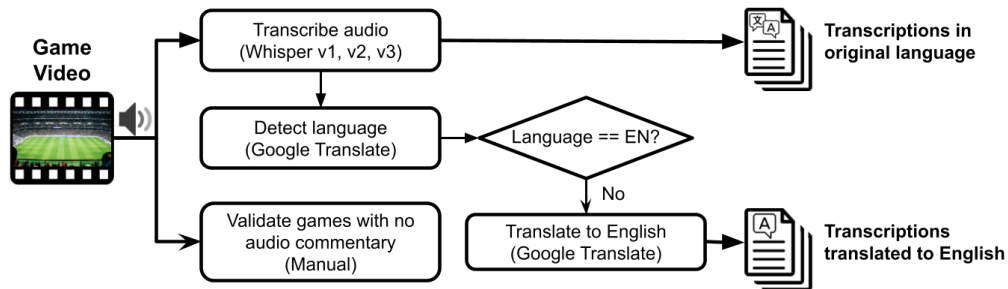
1 Introduction

Figure 1: The pipeline for generating a multilingual commentary dataset from soccer game videos, incorporating different Whisper versions, language detection and translation.

Sports analytics has progressively embraced technological innovations, to enrich the analysis and understanding of complex sports events. Historically, analysis of sports video footage relied primarily on visual cues: action spotting, player recognition and player tracking were based solely on videos and video frames as images. However, with the advancement in multimodal data integration, the

scope of sports analytics has broadened, encompassing audio and textual data alongside traditional visual input. This integration facilitates a more holistic view of sports events, capturing the nuances of game dynamics that visual data alone might miss.

The SoccerNet dataset [12, 7], initially designed to support video-based analyses such as action spotting, player tracking [5], camera calibration [4], dense video captioning [24], foul recognition [14, 15], and game state reconstruction [31], has emerged as a key resource in sports video analytics. Yet, the rapidly evolving field of sports analytics demands ever more sophisticated tools that can process and interpret the complex interplay of multiple data modalities, including video, audio, and text. In response to this need, we augment the SoccerNet dataset by incorporating state-of-the-art ASR technology to enrich the dataset with textual information derived from live game commentaries. This multimodal approach aims to refine the accuracy of existing tasks such as action spotting and dense video captioning, as well as extends the dataset's usefulness in more complex applications such as sentiment analysis or tactical assessment.

This paper details our augmentation of the SoccerNet dataset to include audio commentary transcriptions, generated with OpenAI's Whisper [25] tool, and translated with Google Translate [13]. The resulting SoccerNet-Echoes dataset serves as a comprehensive toolkit for researchers and practitioners, allowing enhanced interpretation and narrative generation from sports footage. Through the integration of audio commentaries in textual format, SoccerNet-Echoes facilitates a deeper understanding of the contextual aspects of soccer games, thereby enhancing both the analytical capabilities and the viewer's experience.

Contributions. Our contributions are threefold: (i) We augment the SoccerNet dataset with automatically transcribed and translated audio commentaries from soccer game broadcasts in multiple languages, and present this new dataset (SoccerNet-Echoes) as an open-access resource. (ii) We evaluate SoccerNet-Echoes using human-verified ASR from literature and perform quantitative analysis. (iii) We explore the potential applications of SoccerNet-Echoes in various research areas, and highlight the broader implications of adopting a multimodal approach for sports research in general.

2 Background and Related Work

The integration of ASR technology has significantly advanced the analysis and processing of video content, impacting sports research [22, 20, 21, 3]. Initially, video understanding focused primarily on computer vision tasks, such as action recognition and event spotting [32, 33, 29, 2]. Advancements in dense video captioning [18] began to explore the generation of captions for temporally localized activities within untrimmed videos, representing a significant departure from the traditional approach of generating a single caption for short clips. Further evolution in the field saw the incorporation of audio and speech modalities alongside visual data, enhancing video captioning capabilities.

2.1 Early Applications: Action Recognition and Event Detection

Before the integration of ASR, the primary focus in sports video analysis was on visual cues for game action recognition and event detection (spotting) [12, 7]. Researchers began to explore the use of multimodal sports data, combining game audio and video streams to improve the accuracy of action spotting in soccer videos [1, 34]. These studies marked an early recognition of the potential benefits of incorporating audio data alongside traditional video processing, setting the stage for the subsequent integration of ASR technologies in sports game analysis [9].

2.2 Transition to Speech and Language Processing

As the potential of multimodal analysis became evident, subsequent studies began to integrate more sophisticated speech and language processing technologies [10, 11]. Gao et al. [8] utilized ASR to segment and categorize commentary from soccer videos, thereby enhancing key moment extraction and highlight generation. This application of ASR for segmenting commentator speech represented a shift towards leveraging linguistic information to complement visual data. Gautam et al. used captions, text and commentaries extracted from ASR for game summarization [10], and used audio intensity to capture the field excitement [11].

2.3 Multimodal Dense Video Captioning

The application of textual modality in sports video analysis reached a new level with the introduction of dense video captioning tasks, as exemplified by the SoccerNet Challenge [6]. The SoccerNet-Caption dataset [23] leverages rich, timestamped textual commentaries that capture both factual and emotional aspects of the game. Aiming to bridge the gap for fans unable to watch soccer games live by providing engaging summaries that mimic the excitement of real-time commentary, this task demonstrated the growing importance of textual modality in creating immersive fan experiences.

Lashin et al. [19] highlighted the transformative potential of integrating ASR alongside video and audio data in dense video captioning. Their multimodal approach significantly improved event description accuracy, emphasizing the vital contextual cues provided by ASR that often elude video-only analyses. By combining visual information with speech data, their method demonstrated substantial performance enhancements, showcasing the synergistic benefits of leveraging multimodal inputs for comprehensive video understanding. Movie Audio Descriptions (MAD) dataset offers a novel benchmark for video-language grounding tasks, by aligning audio descriptions of mainstream movies with video content [30]. The multimodal approach has since been embraced [28], enriching the scope of video captioning and commentary generation [26, 27], and illustrating the transformative impact of ASR technology in video content analysis and processing.

2.4 Advancements in ASR Technologies

The development of LLM-based ASR technologies [36] further accelerated the use of speech recognition in sports analytics. The GOAL dataset [26], derived from SoccerNet videos, comprises 80 full-game videos transcribed into raw text using the Azure ASR toolkit, then meticulously curated by English-speaking, soccer-knowledgeable annotators. 20 games were selected after quality filtering, and annotation tasks included proofreading, aligning text with video timelines, and annotating knowledge entities, ensuring comprehensive linguistic and visual analysis. Ikeda et al. [17] leveraged ASR alongside Whisper [36] and a speech recognition model trained on the extensive Japanese audio corpus ReazonSpeech [35] to transcribe commentary from 134 Japanese Major League Baseball (MLB) highlight videos. To address noise challenges, Whisper transcripts underwent manual labeling, while ReazonSpeech transcripts were labeled using keyword techniques, thereby improving dataset quality and reducing time overheads. These approaches underscore a growing trend in leveraging ASR technology to create rich datasets for detailed examination of both linguistic and visual elements in sports commentary.

2.5 Broader Applications and Future Directions

The integration of ASR technology into soccer video analysis has followed a trajectory from enhancing basic action recognition to enabling sophisticated, multimodal interpretations of complex events. The evolution of this technology has not only improved the analytical capabilities of researchers but has also significantly enhanced the viewing experience for fans worldwide. Beyond soccer, the integration of ASR has also influenced broader video analysis tasks. Hessel et al. [16] explored combining ASR and visual features to generate captions for instructional videos, highlighting how ASR can aid in distinguishing between similar actions through linguistic cues. Sattar et al. [27] focused on identifying events in cricket games by combining commentary text obtained from ASR with visual data and cues such as replays, bowler and umpire positions.

These applications suggest potential future directions where ASR could be integrated into various types of content beyond sports, enriching content accessibility and understanding across domains. As ASR technology continues to advance, its applications in video analysis are expected to expand, further revolutionizing the field and providing deeper insights into the intricate dynamics of media content. However, it is important to acknowledge that despite the advancements, ASR technology is not flawless. Automated capture introduces uncertainty and errors in the ground truth data. Nonetheless, its cost-effectiveness and scalability make ASR a promising candidate for widespread use.

3 Dataset Curation

Our comprehensive approach to curating a multilingual soccer commentary dataset, which includes the automated transcription and translation of commentaries, is illustrated in Figure 1. Below, we detail the curation of the SoccerNet-Echoes using the illustrated methodology.

3.1 Sources and Collection

We used all 1100 game half videos from the SoccerNet [12] dataset. These correspond to 550 games from 6 different leagues and 4 different seasons, as depicted in Figure 2. The games were narrated live by commentators speaking one of 10 different languages. The distribution of the original language of the broadcast game audio is provided in Figure 3. We automatically extracted commentaries in textual format following the procedure described below.
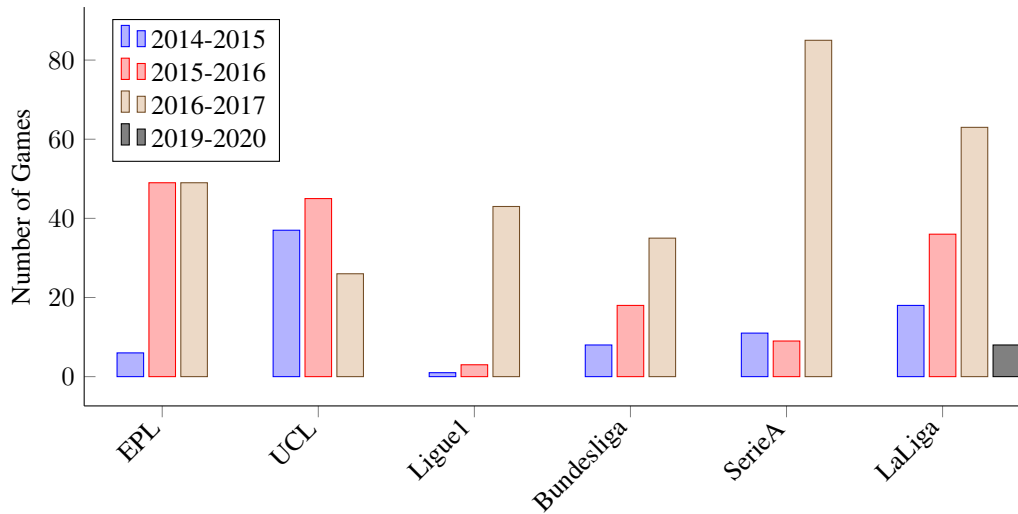
Figure 2: **Number of games** per league and season in the SoccerNet dataset (550 in total).
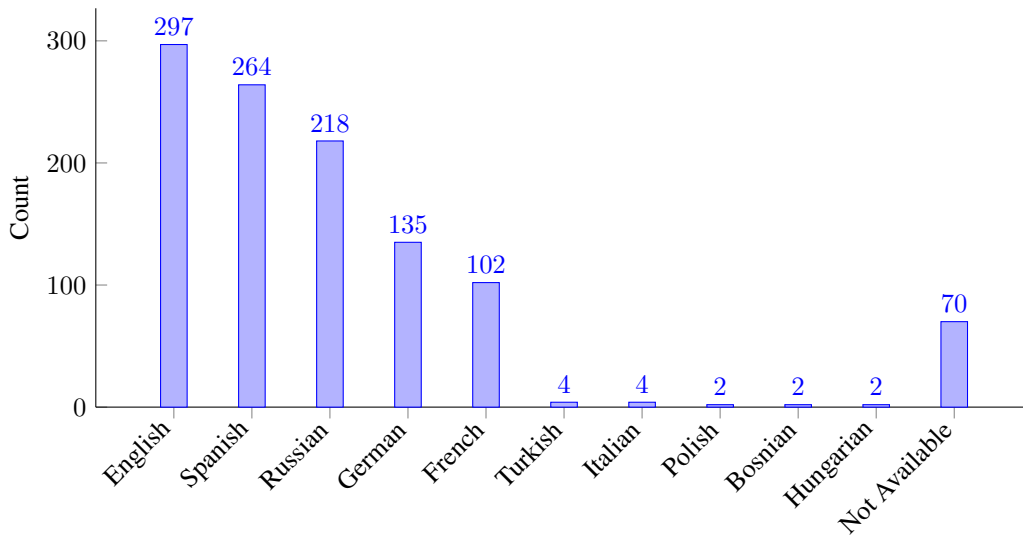
Figure 3: **Language distribution** of the original broadcast audio for each game half, identified using Google Translate and the Whisper language detection model (1100 in total).

3.2 Transcriptions

We used OpenAI's Whisper large-v1[1], large-v2[2], and large-v3[3] ASR models to transcribe the commentator speech from the game audio into text, with the default parameters provided in the original GitHub implementation (commit: `ba3f3cd`) [25]. Initially, the ASR models were used to process all games regardless of the presence of audible human commentary. By default, Whisper models recognize the audio language from the first 30 seconds of the input, and assume that the rest of the audio is in the same language. It should be noted that the model's capability to accurately identify entity names (players, teams, stadiums, etc.) is limited. We performed explicit language detection for all games using Whisper-v2, the resulting language distribution is depicted in Figure 3. Figure 4 presents an example transcription using Whisper from original game audio in English.

| (a) | (b) | (c) | (d) | (e) |

Automatic English Transcription

Frame a to e: "Here is Coman. I wonder if the referee's going to book him for that because that looked like a blatant dive really."
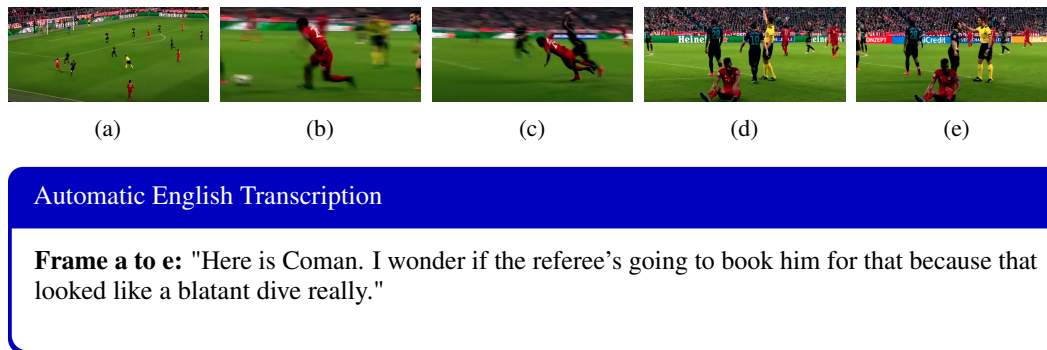

Figure 4: Example transcription using Whisper (original audio in English). Key frames are shown to represent the corresponding video segment.

Manual validation of videos without commentary. As shown in Figure 3, 70 game half videos in the SoccerNet dataset lack audio commentary and therefore had empty ASR outputs. We manually inspected these assets to ensure that they do not in fact contain commentary. Overall, 56 videos were confirmed not to have game audio at all, and 14 videos were confirmed to have game audio but without commentary (only stadium). The detailed list of videos in the SoccerNet dataset without audio commentary is released along with the SoccerNet-Echoes dataset as a spreadsheet.

3.3 Translations

We used the language detection output from Whisper to filter non-English commentaries, and translate the non-English transcriptions into English using Google Translate [13]. This choice was made due to Google Translate's accessibility, ease, and comprehensive language support. Google Translate generally provides reliable translations, particularly for common languages and everyday communication. However, its accuracy can vary depending on factors such as text complexity and linguistic nuances. Figures 5 and 6 present example transcriptions using Whisper and translations to English using Google Translate (from original game audio in German and Russian, respectively).

3.4 Final Public Dataset

The SoccerNet-Echoes dataset and relevant code are publicly released on GitHub under `https://github.com/SoccerNet/sn-echoes`. The dataset is organized as multiple folders under the *Dataset* directory, grouped by league, season, and game. Figure 9 presents an overview of the directory structure. Each ASR JSON file contains the transcribed (and translated where applicable) commentary segments for each game half, organized under the "segments" key, with each segment identified by a unique index within the respective half. Every segment records the start and end time in seconds, which delineate the temporal boundaries of the commentary, along with the transcribed

---

[1] `https://huggingface.co/openai/whisper-large`
[2] `https://huggingface.co/openai/whisper-large-v2`
[3] `https://huggingface.co/openai/whisper-large-v3`

(a) (b) (c) (d) (e)

Automatic German Transcription and English Translation

Frame a to e (Transcription): "Spiel für RB Leipzig, die Mannschaft spielt in weiß und rot Borussia Dortmund im ersten"

Frame a to e (Translation): "Game for RB Leipzig, the team plays in white and red Borussia Dortmund in the first"

Figure 5: Example transcription using Whisper and translation to English using Google Translate (original audio in German). Key frames are shown to represent the corresponding video segment.

(a) (b) (c) (d) (e)

Automatic Russian Transcription and English Translation

Frame a to e (Transcription): "Ну что, похоже будет прямой удар. Мурель попадает в Лоподулу, который, по его мнению, играл рукой. Но Лоподулу сразу подхватывает мяч. Все-таки, да, подумав, подумав, Масимилиану Арате назначает штрафной. Он послушал выгон помощника. Показывает Лоподулу желтую карточку."

Frame a to e (Translation): "Well, it looks like it's going to be a direct hit. Murel ends up in Lopodula, who, in his opinion, played with his hand. But Lopodulu immediately picks up the ball. Still, yes, after thinking, after thinking, he appoints Masimiliana Arata penalty. He listened to the assistant's drive. Shows Lopodul a yellow card."

Figure 6: Example transcription using Whisper and translation to English using Google Translate (original audio in Russian). Key frames are shown to represent the corresponding video segment.

speech, which provides a textual representation of the commentary content. Figure 10 presents the structure of the ASR JSON files.

4   Evaluation

For evaluating the transcription and translations in the SoccerNet-Echoes dataset, we conducted an analysis that uses Word Error Rate (WER), Character Error Rate (CER), BLEU score, and word count as metrics. These metrics are crucial for discerning linguistic richness and accuracy.

4.1   Comparison with Verified Transcriptions

To evaluate the transcription performance, we conducted a comparative analysis using manually verified transcriptions from the GOAL dataset [26]. This dataset comprises human-verified transcriptions from 40 game half videos across 20 games with original commentary in English from the SoccerNet

dataset. We assessed the transcription performance of Whisper large-v1/v2/v3 on these 40 videos against ground truth transcriptions from the GOAL dataset using WER, CER, and BLEU score as metrics. The results are presented in Table 1.

Model	WER	CER	BLEU
Whisper large-v1	0.443	0.261	54.50
Whisper large-v2	0.458	0.269	52.59
Whisper large-v3	0.551	0.341	47.97

Table 1: Transcription performance for different Whisper models [25] against ground truth information from the GOAL dataset [26], averaged over the 20 games for which ground truth transcriptions are available.

4.2 Model Selection

We implemented a "Unique Word Count" heuristic as a criterion to identify the most effective ASR model among the different Whisper versions. This approach facilitated the selection of the best-performing model for each game half based on the diversity of vocabulary in the transcriptions, and proved particularly valuable as a heuristic for assessing model performance in scenarios prone to repeated content, often manifesting as hallucinations (erroneously repeated phrases in the transcription, which are not actually present in the audio). This metric effectively captures the ability of ASR models to generate diverse linguistic outputs, which is crucial for minimizing the impact of such repetitions.

For each game half video, we selected the model with the highest unique word count as the "best" model for further analysis and application. This selection criterion is anchored on the premise that a higher diversity in word usage is indicative of reduced hallucinatory repetitions and, by extension, a more robust transcription performance in diverse acoustic environments. Table 2 presents the average unique word ratio (unique word count divided by the the number of total words) for different Whisper models, averaged over the videos for which the model was selected to be the "best". A pie chart depicting the distribution of selected Whisper models is given in Figure 7.

Model	Number of Videos	Average Unique Word Ratio
Whisper large-v1	316	0.311
Whisper large-v2	231	0.316
Whisper large-v3	483	0.370
Mixed Selection	1030	0.340

Table 2: Average unique word ratio (number of unique words / number of total words) for different Whisper models. "Mixed Selection" represents the overall weighted average across a total of 1030 game half videos with valid commentary, using the "best" model for each video.
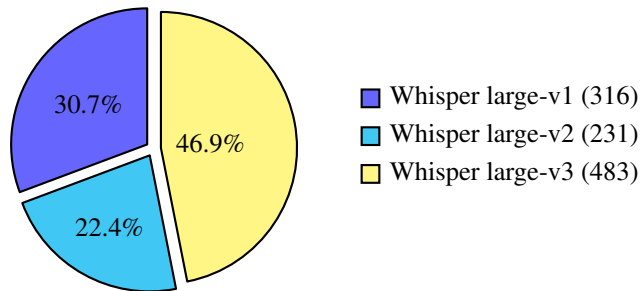

Figure 7: Distribution of the selected Whisper models, for a total of 1030 game half videos with valid commentary.

4.3 Vocabulary Analysis

We conducted an in-depth examination of the linguistic patterns in the soccer game commentaries to identify prevalent verb-noun pairs, which are key to understanding the action dynamics that are described. Utilizing Natural Language Processing (NLP) techniques, we parsed the transcriptions to extract named entities and specific grammatical structures, focusing on the interactions between players and teams. We then applied dependency parsing models to determine the dominant actions by identifying root verbs and their direct objects, providing clarity on the primary activities depicted.

We conducted a sunburst visualization to represent the frequency and distribution of verb-noun combinations, displaying verbs as primary segments with corresponding nouns as sub-segments. This visualization, exemplified for one game half in Figure 8, not only highlights predominant actions but also showcases vocabulary diversity. Such analyses offer insights into sports broadcasting narrative styles and can guide improvements in automated commentary systems.

(a) Ground truth transcription from GOAL dataset
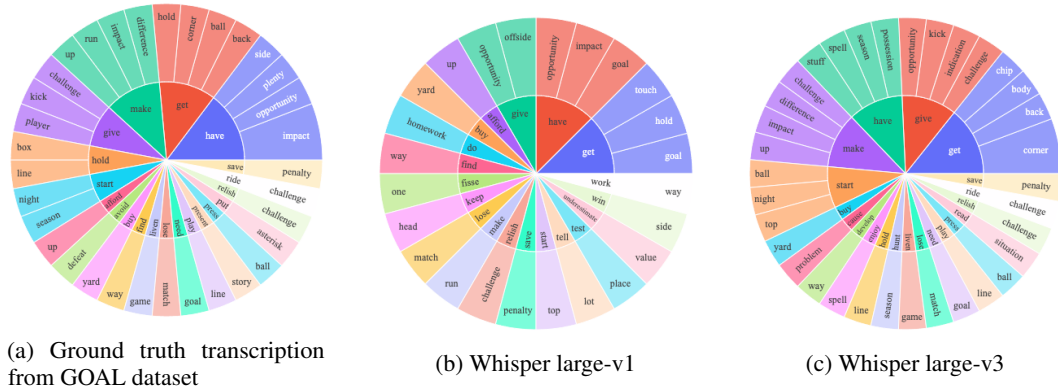
(b) Whisper large-v1

(c) Whisper large-v3

Figure 8: Sunburst plots representing the frequency of verb-noun combinations in the audio commentary transcription for one game half.

5 Discussion

5.1 Dataset Applications

The augmentation of the SoccerNet dataset to include ASR data significantly enriches the multimodal nature of the dataset, enabling a broad range of applications which can leverage the combined strengths of video, audio, and now textual data derived from spoken commentary. These applications are fundamentally enabled by *enhanced content understanding*, i.e., the possibility to train automated systems which can more effectively understand, interpret, and generate soccer-related multimedia content, including an increased contextual awareness for actions, in-game events, highlights/statistics, and entities (e.g., teams, players, locations). Below, we discuss several potential applications of the SoccerNet-Echoes dataset.

Multi-modal event detection: The integration of ASR data can enable more sophisticated and accurate event detection mechanisms. Combining audio cues (such as crowd noise and commentator excitement) and textual triggers from the transcription (such as specific phrases indicating goals or fouls) with visual data can improve the precision and recall of event detection. Such integration is pivotal for real-time analytics, automated highlight generation, and conducting more detailed statistical analysis. The transcription example depicted in Figure 5 showcases the advantages of ASR in this context. In scenarios where the sole analysis of video frames (e.g., based on the zoomed-out shots of the soccer pitch as shown in Figures 5a-5e) might fail to yield detailed information, ASR can provide contextual information, and allow for the extraction of additional details (such as the identification of the teams, and whether they are wearing home or away jerseys), which might not be discernible from the visual data alone.

Game summarization: Automated systems can generate insightful and context-rich summaries of soccer games using the textual modality. This involves not just identifying key events, but also understanding their significance within the game's narrative, as well as the entities involved. For

example, the frequency with which a player's name is mentioned during a crucial moment in the game can indicate the level of their influence, which can be used for assigning an appropriate amount of the overall word budget for the player in the description of the action.

Automated soccer commentator: Commentary datasets such as SoccerNet-Echoes up exciting possibilities for the development of automated real-time soccer game commentator systems. With increasingly more datasets available for training, models can be trained to create more realistic and contextually relevant, but also dynamic and captivating commentary, potentially offering elevated levels of immersion and engagement for the fans.

Tactical analysis: In certain cases, the ASR data can also provide a context for tactical analysis, by enabling an understanding of the discussions made by commentators based on the tactical adjustments made by the coaches during soccer games. In this sense, spoken commentary provides a layer of strategic insight that is typically not captured by video and audio alone. These insights can then also be integrated with various audio cues (such as the audio intensity levels from the stadium) to pinpoint and map tactical highlights to important fan moments within the game.

These applications demonstrate the significant potential of the SoccerNet-Echoes dataset to contribute to sports research and broadcasting. Using the power of multimodal data, researchers and developers can create more sophisticated tools that address a wide range of needs within the sports community.

5.2 Limitations and Future Work

Our use of deep learning models for ASR and batch translation for the curation of the SoccerNet-Echoes dataset have also introduced a number of limitations. We aim to address several of the following challenges in future work.

Transcription accuracy: The inference capability and accuracy of the ASR models are inherently constrained by their design, occasionally leading to errors in transcription.

Hallucinations: Whisper models are known to be prone to hallucinations (unwarranted repetition of phrases and words). During the curation of the SoccerNet-Echoes dataset, we have observed hallucinations across all Whisper ASR models, especially under conditions where the audio inputs were devoid of human speech, were excessively noisy, or contained musical elements. Such conditions significantly challenge transcription accuracy of the models, leading to the anomalous generation of repeated phrases. These repetitions not only degrade the quality of the transcription, but also affect the usability of the transcribed text in downstream applications, such as subtitle generation or voice-driven gameplay interaction. By analyzing the occurrences of repeated words under various audio conditions, we aimed to understand the strengths and limitations of different models.

Audio quality: As mentioned above, we have seen that the quality of the audio to be transcribed significantly impacts the reliability of the transcriptions. Implementing advanced audio pre-processing techniques to filter out background noise and music could enhance the clarity of the input signal for ASR systems. Combining Whisper with other technologies such as Voice Activity Detection (VAD) could also help reduce ASR errors and hallucinations.

Human verification: The absence of human-verified annotations to serve as ground truth poses a substantial challenge for all ASR datasets. Generating such annotations is prohibitively expensive, thus limiting the ability of researchers to comprehensively verify and refine ASR datasets. However, this limitation is also critical to address, in order to advance the reliability and applicability of our SoccerNet-Echoes dataset. We therefore plan to invest in the curation of human-verified annotations, for a subset of the assets in SoccerNet-Echoes, as future work. Despite being expensive, we believe that such a dataset could provide a valuable benchmark for assessing and improving ASR accuracy. Efforts could also involve collaborations with various academic institutions and community-sourcing the annotations.

Batch translations: Machine translation systems, such as Google Translate, are not infallible and their limitations must be acknowledged. When translations are performed on entire texts at once, they can produce different outputs compared to translations of specific, smaller segments. For instance, as depicted in Figure 6, the Russian term "штрафной" was erroneously translated as "penalty kick" when the entire game half was translated, contrasting with the accurate translation "free kick" when only the segment was translated. This discrepancy underscores the contextual challenges faced by machine translation.

6   Conclusion

The augmentation of the SoccerNet dataset using ASR technology marks a pivotal advance in the domain of sports analytics, providing a richer and more integrated approach to understanding soccer games. The inclusion of multimodal data not only aids in the accurate detection and description of in-game events but also enriches the dataset's applicability across various analytical tasks such as sentiment analysis and tactical assessments. Despite the limitations associated with ASR, such as potential inaccuracies and hallucinations under challenging audio conditions, the benefits presented by the SoccerNet-Echoes dataset are substantial. Future work will focus on refining ASR accuracy through the curation of a human-verified annotation subset and the implementation of advanced audio pre-processing techniques. By continually improving the dataset's quality and the methodologies used to analyze it, SoccerNet-Echoes is poised to significantly influence the development of automated systems for sports broadcasting and analytics, enhancing the consumption and comprehension of sports events globally. This work not only underscores the transformative impact of integrating ASR into sports video analysis but also sets a precedent for future research in the field, promising deeper insights and more effective tools for researchers, sports analytics professionals, and enthusiasts.

References

[1] M. Barnard, J.-M. Odobez, and S. Bengio. Multi-modal audio-visual event recognition for football analysis. In *IEEE XIII Workshop on Neural Networks for Signal Processing (IEEE Cat. No.03TH8718)*, pages 17–19. IEEE, 2003. ISBN 978-0-7803-8177. doi: 10.1109/NNSP.2003. 1318046.

[2] Bruno Cabado, Anthony Cioppa, Silvio Giancola, Andrés Villa, Bertha Guijarro-Berdinas, Emilio J Padròn, Bernard Ghanem, and Marc Van Droogenbroeck. Beyond the premier: Assessing action spotting transfer capability across diverse domains. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), CVsports*, 2024.

[3] Yuh-Lin Chang, Wenjun Zeng, I. Kamel, and R. Alonso. Integrated image and speech analysis for content-based video indexing. In *Proceedings of the Third IEEE International Conference on Multimedia Computing and Systems*, pages 17–23. IEEE, 1996. ISBN 978-0-8186-7438. doi: 10.1109/MMCS.1996.534992.

[4] Anthony Cioppa, Adrien Deliège, Silvio Giancola, Bernard Ghanem, and Marc Van Droogenbroeck. Scaling up SoccerNet with multi-view spatial localization and re-identification. *Sci. Data*, 9(1):1–9, Jun. 2022. doi: 10.1038/s41597-022-01469-1. URL https://doi.org/10. 1038/s41597-022-01469-1.

[5] Anthony Cioppa, Silvio Giancola, Adrien Deliege, Le Kang, Xin Zhou, Zhiyu Cheng, Bernard Ghanem, and Marc Van Droogenbroeck. SoccerNet-tracking: Multiple object tracking dataset and benchmark in soccer videos. In *IEEE Int. Conf. Comput. Vis. Pattern Recognit. Work. (CVPRW), CVsports*, pages 3490–3501, New Orleans, LA, USA, Jun. 2022. Inst. Electr. Electron. Eng. (IEEE). doi: 10.1109/cvprw56347.2022.00393. URL https://doi.org/10.1109/ CVPRW56347.2022.00393.

[6] Anthony Cioppa, Silvio Giancola, Vladimir Somers, Floriane Magera, Xin Zhou, Hassan Mkhallati, et al. SoccerNet 2023 Challenges Results. *arXiv*, Sept. 2023. doi: 10.48550/arXiv. 2309.06006.

[7] Adrien Deliège, Anthony Cioppa, Silvio Giancola, Meisam J. Seikavandi, Jacob V. Dueholm, Kamal Nasrollahi, et al. SoccerNet-v2: A Dataset and Benchmarks for Holistic Understanding of Broadcast Soccer Videos. In *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pages 19–25. IEEE, 2021. doi: 10.1109/CVPRW53098. 2021.00508.

[8] Xin Gao, Xusheng Liu, Taotao Yang, Guilin Deng, Hao Peng, Qiaosong Zhang, et al. Automatic Key Moment Extraction and Highlights Generation Based on Comprehensive Soccer Video Understanding. In *2020 IEEE International Conference on Multimedia & Expo Workshops (ICMEW)*, pages 06–10. IEEE, 2020. doi: 10.1109/ICMEW46912.2020.9106051.

[9] Sushant Gautam. Bridging Multimedia Modalities: Enhanced Multimodal AI Understanding and Intelligent Agents. In *ICMI '23: Proceedings of the 25th International Conference on Multimodal Interaction*, pages 695–699. Association for Computing Machinery, New York, NY, USA, Oct. 2023. ISBN 979-840070055-2. doi: 10.1145/3577190.3614225.

[10] Sushant Gautam, Cise Midoglu, Saeed Shafiee Sabet, Dinesh Baniya Kshatri, and Pål Halvorsen. Soccer Game Summarization using Audio Commentary, Metadata, and Captions. In *NarSUM '22: Proceedings of the 1st Workshop on User-centric Narrative Summarization of Long Videos*, pages 13–22. Association for Computing Machinery, New York, NY, USA, Oct. 2022. ISBN 978-1-45039493-2. doi: 10.1145/3552463.3557019.

[11] Sushant Gautam, Cise Midoglu, Saeed Shafiee Sabet, Dinesh Baniya Kshatri, and Pål Halvorsen. Assisting soccer game summarization via audio intensity analysis of game highlights. In *Proc. 12th IOE Graduate Conference*, pages 25–32. Inst. of Eng. Tribhuvan University, Nepal, Oct. 2022. URL `http://conference.ioe.edu.np/publications/ioegc12/IOEGC-12-004-12009.pdf`.

[12] Silvio Giancola, Mohieddine Amine, Tarek Dghaily, and Bernard Ghanem. SoccerNet: A Scalable Dataset for Action Spotting in Soccer Videos. In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pages 18–22. IEEE, 2018. doi: 10.1109/CVPRW.2018.00223.

[13] Google. Google Translate, Apr. 2024. [Online; https://translate.google.com].

[14] Jan Held, Anthony Cioppa, Silvio Giancola, Abdullah Hamdi, Bernard Ghanem, and Marc Van Droogenbroeck. VARS: Video assistant referee system for automated soccer decision making from multiple views. In *IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Work. (CVPRW)*, pages 5086–5097, Vancouver, Can., Jun. 2023. Inst. Electr. Electron. Eng. (IEEE). doi: 10.1109/cvprw59228.2023.00537. URL `https://doi.org/10.1109/CVPRW59228.2023.00537`.

[15] Jan Held, Hani Itani, Anthony Cioppa, Silvio Giancola, Bernard Ghanem, and Marc Van Droogenbroeck. X-vars: Introducing explainability in football refereeing with multi-modal large language models. In *IEEE Int. Conf. Comput. Vis. Pattern Recognit. Work. (CVPRW), CVsports*, Seattle, WA, USA, Jun. 2024.

[16] Jack Hessel, Bo Pang, Zhenhai Zhu, and Radu Soricut. A Case Study on Combining ASR and Visual Features for Generating Instructional Video Captions. *ACL Anthology*, pages 419–429, Nov. 2019. doi: 10.18653/v1/K19-1039.

[17] Riku Ikeda, Kazuma Sakamoto, and Yoshihiro Ueda. Breaking News System of At-Bat Results From Sports Commentary via Speech Recognition. *IEEE Access*, 12:27199–27209, Feb. 2024. ISSN 2169-3536. doi: 10.1109/ACCESS.2024.3365948.

[18] Ranjay Krishna, Kenji Hata, Frederic Ren, Li Fei-Fei, and Juan Carlos Niebles. Dense-Captioning Events in Videos. In *2017 IEEE International Conference on Computer Vision (ICCV)*, pages 22–29. IEEE, 2017. doi: 10.1109/ICCV.2017.83.

[19] Vladimir Lashin and Esa Rahtu. *Multi-modal Dense Video Captioning*. IEEE Computer Society, Jun. 2020. ISBN 978-1-7281-9360-1. doi: 10.1109/CVPRW50498.2020.00487.

[20] Jinyu Li. Recent Advances in End-to-End Automatic Speech Recognition. *SIP*, 11(1), Apr. 2022. doi: 10.1561/116.00000050.

[21] Yao Lu and Shuyang An. Research on sports video detection technology motion 3D reconstruction based on hidden Markov model. *Cluster Comput.*, 23(3):1899–1909, Sept. 2020. ISSN 1573-7543. doi: 10.1007/s10586-020-03097-z.

[22] Mishaim Malik, Muhammad Kamran Malik, Khawar Mehmood, and Imran Makhdoom. Automatic speech recognition: a survey. *Multimed. Tools Appl.*, 80(6):9411–9457, Mar. 2021. ISSN 1573-7721. doi: 10.1007/s11042-020-10073-7.

[23] Hassan Mkhallati, Anthony Cioppa, Silvio Giancola, Bernard Ghanem, and Marc Van Droogenbroeck. SoccerNet-Caption: Dense Video Captioning for Soccer Broadcasts Commentaries. In *2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pages 17–24. IEEE, 2023. doi: 10.1109/CVPRW59228.2023.00536.

[24] Hassan Mkhallati, Anthony Cioppa, Silvio Giancola, Bernard Ghanem, and Marc Van Droogenbroeck. SoccerNet-caption: Dense video captioning for soccer broadcasts commentaries. In *IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Work. (CVPRW)*, pages 5074–5085, Vancouver, Can., Jun. 2023. Inst. Electr. Electron. Eng. (IEEE). doi: 10.1109/cvprw59228.2023.00536. URL https://doi.org/10.1109/CVPRW59228.2023.00536.

[25] OpenAI. Whisper. GitHub, Apr. 2024. [Online; https://github.com/openai/whisper].

[26] Ji Qi, Jifan Yu, Teng Tu, Kunyu Gao, Yifan Xu, Xinyu Guan, et al. GOAL: A Challenging Knowledge-grounded Video Captioning Benchmark for Real-time Soccer Commentary Generation. In *CIKM '23: Proceedings of the 32nd ACM International Conference on Information and Knowledge Management*, pages 5391–5395. Association for Computing Machinery, New York, NY, USA, Oct. 2023. ISBN 979-840070124-5. doi: 10.1145/3583780.3615120.

[27] Husnain Sattar, Muhammad Shamil Umar, Eeman Ijaz, and Muhammad Umair Arshad. Multi-Modal Architecture for Cricket Highlights Generation: Using Computer Vision and Large Language Model. In *2023 17th International Conference on Open Source Systems and Technologies (ICOSST)*, pages 20–21. IEEE, 2023. doi: 10.1109/ICOSST60641.2023.10414235.

[28] Paul Hongsuck Seo, Arsha Nagrani, Anurag Arnab, and Cordelia Schmid. *End-to-end Generative Pretraining for Multimodal Video Captioning*. IEEE Computer Society, Jun. 2022. ISBN 978-1-6654-6946-3. doi: 10.1109/CVPR52688.2022.01743.

[29] Huang-Chia Shih. A Survey of Content-Aware Video Analysis for Sports. *IEEE Trans. Circuits Syst. Video Technol.*, 28(5):1212–1231, Jan. 2017. doi: 10.1109/TCSVT.2017.2655624.

[30] Mattia Soldan, Alejandro Pardo, Juan León Alcázar, Fabian Caba, Chen Zhao, Silvio Giancola, and Bernard Ghanem. Mad: A scalable dataset for language grounding in videos from movie audio descriptions. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 5026–5035, June 2022.

[31] Vladimir Somers, Victor Joos, Silvio Giancola, Anthony Cioppa, Seyed Abolfazl Ghasemzadeh, Floriane Magera, Baptiste Standaert, Amir Mohammad Mansourian, Xin Zhou, Shohreh Kasaei, Bernard Ghanem, Alexandre Alahi, Marc Van Droogenbroeck, and Christophe De Vleeschouwer. SoccerNet game state reconstruction: End-to-end athlete tracking and identification on a minimap. In *IEEE Int. Conf. Comput. Vis. Pattern Recognit. Work. (CVPRW), CVsports*, Seattle, WA, USA, Jun. 2024.

[32] Khurram Soomro, Amir Roshan Zamir, and Mubarak Shah. UCF101: A Dataset of 101 Human Actions Classes From Videos in The Wild. *arXiv*, Dec. 2012. doi: 10.48550/arXiv.1212.0402.

[33] Richard Szeliski. *Computer Vision*. Springer International Publishing, Cham, Switzerland, 2022. ISBN 978-3-030-34372-9. URL https://link.springer.com/book/10.1007/978-3-030-34372-9.

[34] Bastien Vanderplaetse and Stéphane Dupont. Improved Soccer Action Spotting using both Audio and Video Streams. In *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pages 14–19. IEEE, 2020. doi: 10.1109/CVPRW50498.2020.00456.

[35] Yue Yin, Daijiro Mori, and Seiji Fujimoto. Reazonspeech: A free and massive corpus for japanese asr. In *Proceedings of the 29th Annual Conference of the Language Processing Society (NLP 2023)*, March 2023.

[36] Zixing Zhang, Jürgen Geiger, Jouni Pohjalainen, Amr El-Desoky Mousa, Wenyu Jin, and Björn Schuller. Deep Learning for Environmentally Robust Speech Recognition: An Overview of Recent Developments. *ACM Trans. Intell. Syst. Technol.*, 9(5):1–28, Apr. 2018. ISSN 2157-6904. doi: 10.1145/3178115.

APPENDIX

Figure 9 presents an overview of the SoccerNet-Echoes dataset directory under `https://github.com/SoccerNet/sn-echoes`.

```
≋ Dataset
 └─■ whisper_v1
    └─♔ england_epl
       └─🗓 2014-2015
          └─⚽ 2016-03-02-23-00 Liverpool 3-0 Manchester City
             └─☁ 1_asr.json
             └─☁ 2_asr.json
          └─ ...
       └─🗓 2015-2016
    └─ ...
    └─♔ europe_uefa-champions-league
    └─ ...
    └─♔ france_ligue-1
    └─ ...
    └─♔ germany_bundesliga
    └─ ...
    └─♔ italy_serie-a
    └─ ...
    └─♔ spain_laliga
    └─ ...
 └─■ whisper_v1_en
    └─ ...
 └─■ whisper_v2
    └─ ...
 └─■ whisper_v2_en
    └─ ...
 └─■ whisper_v3
    └─ ...
 └─■ whisper_v3_en
    └─ ...
```

Figure 9: SoccerNet-Echoes dataset directory structure.

Figure 10 presents the structure of the ASR JSON files in the dataset.

```
{
  "segments": {
    (int) <segment index>:[
        (float) <start time in seconds>,
        (float) <end time in seconds>,
        (string) <commentary text>
    ],
    ....
  }
}
```

Figure 10: Structure of the ASR JSON files in the SoccerNet-Echoes dataset.