Journal of Exercise and Health Science, Vol. 02, No. 03, Summer 2022, Page 25-44

Research Paper

Detecting Head Injuries in Football Using Deep Learning Approach with Spatial-Temporal Features in Video Data

Mohsen Esmaeili Sani[1]

1. PhD Student in Sport Management, Mazandaran University-Babolsar, Iran.

Received: 2022/04/22 **Accepted: 2022/10/15**

Abstract

Objective: The aim of this study is to propose a deep learning approach for detecting head injuries in football video data using spatial-temporal features.

Methods: The proposed method employs ResNet-50 architecture and the Temporal Shift Module (TSM) for feature learning and classification. The algorithm is trained with a publicly available soccer video dataset labeled with annotated head injuries. The evaluation of the proposed method is done on a test set that includes 500 football videos, and the evaluation criteria used include overall accuracy, precision, recall, and F1 score.

Results: The proposed algorithm achieves an overall accuracy of 0.986 in detecting head injuries in the test set, which is a significant improvement compared to previous studies in the same field.

Conclusion: The proposed method provides a promising approach for head impact event detection using spatio-temporal features, which could have important implications for sports and medical industries. However, the model requires a large amount of annotated data for training, and future research could focus on addressing limitations such as developing more efficient training methods and incorporating other techniques to identify head injuries outside the camera's field of view.

Keywords: Brain Concussion, Traumatic Brain Injury, Machine Learning, Neural Networks (Computer), Video Recording, Pattern Recognition, Automated, Soccer.

1. Email: mhx71@yahoo.com

Introduction

Head injuries in soccer can have acute and long-term consequences (Beadwin et al., 2021). Acute outcomes include concussions, which account for up to 22% of football injuries. Long-term consequences include post-concussive syndrome (PCS), chronic neurocognitive impairments such as mild cognitive impairment (MCI), and chronic traumatic encephalopathy (CTE) (Beadwin et al., 2021). Heading the ball is associated with lower cognitive performance and microstructural brain damage in high school, adult amateur, and professional soccer players (Stewart et al., 2017).

The risk of permanent functional or structural brain damage as a result of head impacts during soccer can be reduced by using lighter balls or modifying playing techniques. However, head injuries have historically been underrepresented and field assessment by non-medical and medical professionals remains challenging (Beadwin et al., 2021).The potential consequences of a head injury in football are serious and can affect short- and long-term health. Taking measures to reduce the risk of head injury during the game is very important. Exposure to repeated head impacts in sports may not only increase the risk of sustaining an acute brain injury such as type 1 and type 2 concussions, but also lead to increased long-term brain changes (Beckwith et al., 2013; Montenegro et al., 2017; Stemper et al., 2019). However, there are limited data to quantify the correlation between impact exposure and brain health outcomes. In soccer, headers are common because players often use their heads to redirect the ball. In fact, soccer heading accounts for about 90% of head impacts in soccer, and the remaining impacts are mostly unintentional player-to-player or head impacts (Press & Rawson, 2017). It is unclear whether intentional soccer heading, which is more frequent but less severe than unintentional head impacts, may have detrimental effects on the brain. Exposure to a controlled concussion session is associated with increases in reported concussion symptoms, changes in postural control, and increases in cortisol inhibition with impaired memory performance. White matter microstructural abnormalities and neurocognitive impairment have been found for players reporting long-term exposure of 885 to 1,800 heads per year (Haran et al., 2013; Lipton et al., 2013). However, some studies have not found significant neurocognitive performance or neuropsychological changes associated with short-term exposure to soccer heading (Kontos et al., 2011; Stephens et al., 2010). The use of self-reported effect estimates in some studies could be a potential reason for the mixed results in the articles. Such reports of subjective exposure may not provide an accurate estimate of head impact (Sandmo et al., 2021). Because of the inconclusive results of repeated exposure to football headers, longitudinal research is recommended to link accurate measures of exposure to brain outcomes (Rodrigues et al., 2016). Therefore, the current strategies to mitigate head injury risks, such as the use of lighter balls or modified playing techniques, are insufficient. The limitations in accurately quantifying head impact exposure and correlating it with brain health outcomes exacerbate the problem. Soccer heading, responsible for the majority of head impacts in the sport, presents a paradoxical scenario where its frequent yet less severe impacts compared to unintentional head collisions are suspected to be detrimental to brain health. However, studies yield mixed results, partly due to reliance on self-reported impact estimates, highlighting the need for objective, accurate exposure measurement methods.

One common thread in these studies is that they use head kinematics data obtained from FE simulations/ wearable devices/ head instrumentation as input for their deep learning models to either predict strains in the brain or detect impact to the head. Related to head kinematics, video analysis has also been used in the past. For example, Sanchez et al. evaluated laboratory reconstruction videos of head impacts collected from professional football games. The videos were generated from a high-speed camera recording at 500 frames per second. These videos were not used to predict or compute head kinematics but were analyzed to identify a time region of applicability (RoA) for head kinematics and for application to FE brain models to determine MPS and cumulative strain damage measure (CSDM). Sensitivity comes at the cost of a high false positive rate, while increasing the threshold to improve accuracy can lead to an increased false negative threshold (Qiu et al., 2018; Wang et al., 2021). Furthermore, limited kinematic accuracy in sensors leads to uncertainty in estimated head accelerations for head impact (Sigmond et al., 2016; Weuw et al., 2016). Some sensors have combined the simple acceleration threshold method with additional filtering algorithms to remove false positive bands. However, laboratory and field evaluation studies have shown poor performance of such an algorithm (Allison et al., 2014; Nevins et al., 2016; Sigmond et al., 2016). Table (1) shows a summary of sensor-based head impact studies in football. Few studies have quantified the impact detection performance of the used sensors and found limited sensitivity and accuracy. Additionally, wearable head impact sensors are costly to deploy on a large scale and track exposure, and may not always be readily adopted or worn regularly by sports participants.

Given the limitations of impact sensors, video analysis is recommended to improve the accuracy of impact exposure data (Patton et al., 2020). Most studies use video data only to validate the registration of sensory features (Hanlon and Beer, 2012; Kakse et al., 2016; Patton et al., 2020). This is limited in the current research because this approach does not identify potential false negatives and may underestimate the effect. Therefore, other studies have performed an independent analysis of the video to identify all potential exposure events based on human reviewer observations (Campbell et al., 2020; Kiwa et al., 2018; Miller et al., 2020). Video information is also used to extract contextual factors that characterize head impacts, such as impact position, object impact, and impact. However, video analysis is a time-consuming process that requires considerable human resources. In a previous study, 14 trained raters reviewed 163 hours of video to fully validate 217 head impacts (Kyoa et al., 2018). Generating large-scale concussion exposure data using stand-alone video analysis would be a costly and time-consuming task. Therefore, this research is imperative to address the critical gap in effectively detecting and analyzing head impacts in football, thereby enhancing player safety and health outcomes. The limitations of current head impact sensors, including their kinematic accuracy and high false-positive rates, necessitate the exploration of alternative methods such as video analysis for more accurate impact detection. Moreover, the costly and labor-intensive nature of manual video analysis for large-scale data highlights the urgent need for automated, efficient approaches.

Deep learning is a part of machine learning based on artificial neural networks and has been shown to be very effective in solving complex problems in the area of computer vision, natural language processing, drug discovery, medical image analysis, etc. Automatic analysis of sports games using video information has been widely studied in computer vision research. Computer vision algorithms, especially deep learning (DL) techniques, have been applied to automate tasks such as player / ball detection and tracking, player pose estimation, game reconstruction, and game statistics generation (Thomas et al., 2017). Recently, deep learning models were used in brain injury biomechanics field as well. Wu et al. used American college football, boxing and mixed martial arts (MMA) datasets along with lab-reconstructed National Football League impacts dataset to develop a deep learning model to predict 95th percentile max principal strain of the entire brain and the corpus callosum along with fiber strain of the corpus callosum. To address this critical issue, researchers have turned to deep learning methodologies. One notable study by Hasija and Takhounts (2022) explored predicting head angular kinematics directly from crash simulation videos, without relying on wearable devices or instrumentation. Their approach involved developing a combined convolutional neural network (CNN) and recurrent neural network (RNN) model using finite element (FE) data. The model successfully predicted time histories of head angular velocities, achieving strong correlations with actual peak angular velocities in the X, Y, and Z components. Zhan et al. used kinematic data generated by FE simulations and those collected from on-field football and MMA using instrumented mouthguards and developed a deep learning head model to predict the peak maximum principal strain (MPS) of every element in the brain. Ghazi et al. developed a convolutional neural network (CNN) to instantly estimate element-wise distribution of peak maximum principal strain of the entire brain using two-dimensional images of head rotational velocity and acceleration temporal profiles as input to CNN model. Further, Bourdet et al. developed a deep learning model with linear accelerations and linear velocities from helmet tests as input to the model to predict maximum Von Mises stress within the brain. In addition to predicting strains and stresses in the brain, deep learning models have also been developed to detect impacts to the head in American Football. In a similar vein, Gabler et al. undertook a comprehensive assessment of various machine learning (ML) models and developed an Adaboost-based ML model to distinguish between genuine head impacts and spurious events. They achieved this using 6DOF head kinematic data derived from a specialized mouthguard sensor. More recently, Raymond et al. harnessed head kinematic data collected from instrumented mouthguards and enriched it with synthetic head kinematic data obtained from finite element (FE) head impacts to detect head impacts using a physics-informed ML model. These research endeavors, like Liu, Liu, and Sun's work, exemplify the innovative applications of machine learning and deep learning techniques in diverse domains, from sports video analysis to head impact detection, ultimately contributing to advancements in their respective fields. In their study, Zhan et al. (2021) introduce a cutting-edge deep learning head model designed to accelerate the computation of brain deformation caused by head impacts, an essential factor in understanding and mitigating traumatic brain injuries. This innovative model, powered by a five-layer deep neural network and feature engineering, delivers rapid and accurate calculations for maximum principal strain in the entire brain, as well as the corpus callosum and fiber strain of the corpus callosum. Notably, the model achieves impressive efficiency, with calculations completed in less than 0.001 seconds, demonstrating its potential for real-time clinical applications and its superiority over traditional finite element models in estimating brain strain across diverse head impact scenarios. Conversely, Rico-González, Pino-Ortega, Méndez, Clemente, and Baca (2023) conduct a systematic review focused on the integration of machine learning (ML) in soccer, a sport renowned for its complexity and the demand for data-driven decision-making. Their exhaustive analysis encompasses 145 identified studies, with a comprehensive examination of 32 selected studies that span three primary categories: injury, performance (encompassing match/league outcomes forecasting, physical/physiological forecasting, and technical/tactical forecasting), and talent forecasting. The review underscores the burgeoning role of ML in soccer, empowered by technological advancements and the vast availability of data. ML models emerge as invaluable assets in aiding team staff in predicting outcomes, optimizing player performance, and navigating the unpredictable nature of soccer. Nevertheless, the review highlights the critical role of data quantity in the efficacy of ML models, emphasizing the need for further research to determine the optimal dataset sizes required for precise predictions in soccer-related applications. These studies collectively showcase the transformative potential of machine learning and deep learning techniques across diverse domains, from brain injury biomechanics to soccer analytics, contributing significantly to advancements in their respective fields.

Rezaei and wiu (2022) stated that video data has two types of information: the visual information contained in each frame of the video as well as the dynamic time information that can be obtained from successive frames. DLR-based research in video understanding follows a general structure for using this spatial and temporal information. A common method involves extracting visual features in the spatial domain from each frame using convolutional neural networks (CNNs), and then temporally summing the features of successive frames to produce a video description (Donahue et al. , 2015; Karapassi et al., 2014;Yu He et al., 2015). The descriptor is then used to train an action classifier. It is a fully data-driven approach where the algorithm is trained on a dataset consisting of video samples of each action.

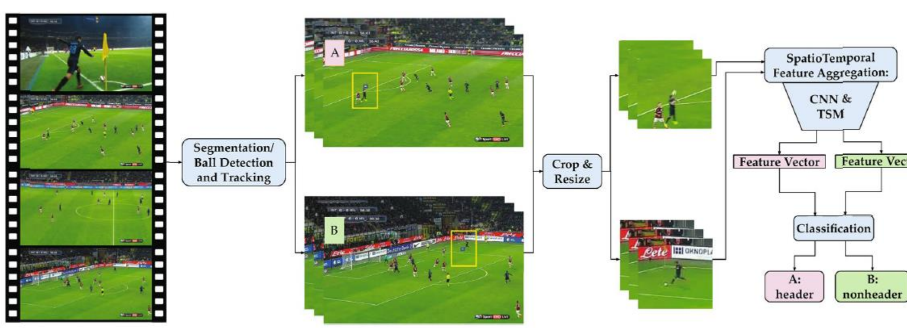

figure 1. An overview of the proposed head blow detection algorithm.

The video is divided into short segments and the position of the ball in each segment is detected and tracked. Each frame is then cropped around the ball position. Spatio-temporal features of each cropped video segment are extracted using a Convolutional Neural Network (CNN) and Time Shift Module (TSM).

Then, the extracted feature vector is classified as a head hit or no head hit event in the last step of the algorithm (Rezaei & wiu, 2022)
Figure (1) shows the proposed framework of Rezaei and wiu (2022), which includes 5 steps. The input video is divided into short segments, and in each segment, the position of the ball is detected using a deep learning object detection algorithm. A tracking ball algorithm is used to improve the estimation of the ball position in the located position. Using the estimated ball position, each box is cropped around the ball position. Then, the spatial and temporal information of all frames in each video segment are extracted and aggregated into a feature vector. Similar to the ball detection network, a spatio-temporal feature aggregation network based on deep learning is used, which is trained using the soccer header dataset. Finally, a neural network classifier is trained to classify the visual-temporal features as a nodding or non-nodding event. The summary of the performance evaluation of Rezaei and wiu (2022) algorithm is presented in table (1). Now, let’s bridge this research to football. Imagine a scenario where deep learning algorithms analyze football game footage, capturing spatial-temporal features. These features could include player movements, impact forces, and head motions. By training models on annotated video data, we can potentially identify patterns associated with head injuries. The integration of spatial and temporal information allows us to detect abnormal head movements, even in real-time game situations. Inspired by recent advancements, a two-stream deep learning architecture called SpikeConvFlowNet could be employed. This model processes RGB frames and their optical flow data to extract spatiotemporal features. By analyzing player interactions, tackles, and collisions, it aims to flag instances that pose a risk of head injuries. The fusion of visual and motion cues enhances its predictive capabilities. In the ongoing battle against head injuries in football, deep learning offers hope. By harnessing spatial-temporal features from video data, we can create early warning systems that protect athletes from the unseen dangers of the game. As technology evolves, our ability to safeguard players and prevent long-term consequences grows stronger.

Table 1- Summary of the performance evaluation of the source algorithm: (Rezaei and wiu, 2022)

Value	Metric
0.971	Accuracy
0.974	Precision (Header)
0.964	Recall (Header)
0.969	F1-Score (Header)
0.968	Precision (Non-Header)
0.977	Recall (Non-Header)
0.973	F1-Score (Non-Header)

The prevalence of head injuries in football, with their significant acute and long-term health impacts, has elevated the urgency for developing more effective detection and analysis strategies. Current methodologies, predominantly based on professional field assessments and the deployment of wearable sensors, are riddled with inaccuracies and limitations. These conventional techniques not only fail to comprehensively capture the extent of head impacts but also introduce considerable logistical and financial challenges for large-scale application. This situation has highlighted a critical need for innovative approaches that can accurately and efficiently identify head impacts during gameplay. Deep learning emerges as a potent solution, offering advanced computational power and the capability to process complex data sets. This research is centered on harnessing deep learning to extract and analyze spatio-temporal features from video data, aiming to provide a scalable and reliable method for enhancing player safety and mitigating the risks associated with head injuries. By utilizing cutting-edge libraries and frameworks such as TensorFlow or PyTorch, coupled with the sophisticated ResNet-50 architecture, this study leverages the latest technological advancements to ensure high model accuracy and generalizability. The core objective of this research is to develop a deep learning algorithm capable of detecting head impact events in football by analyzing video footage. This method intends to surpass the inherent constraints of existing diagnostic practices by utilizing the rich spatial and temporal information embedded within videos of football matches. In doing so, it seeks to enable the early detection of head injuries, potentially diminishing the occurrence of long-term damage and enhancing recovery prospects for impacted players. By adopting this deep learning approach, the research aspires to revolutionize injury diagnosis within the realm of sports, specifically addressing the urgent concerns surrounding head injuries in football. The implementation of sophisticated tools and architectures underscores a commitment to achieving unparalleled levels of accuracy and applicability, setting a new standard for player safety and health preservation in sports.

Methodology

Study Design and Participants

This study employs a quantitative research design, utilizing a deep learning approach to detect head injuries in football video data. The research design is observational, where the algorithm analyzes existing video data without manipulating the environment or conditions. The participants in this study comprise the subjects within the publicly available soccer video dataset, which includes 2000 videos of soccer games totaling 50 hours of playtime. These videos feature professional and amateur soccer matches with annotated head injuries. The sample size was determined based on the availability of high-quality, annotated video data to ensure a comprehensive training and validation process for the deep learning model. This dataset's extensive nature allows for a significant variety of head injury scenarios, contributing to the robustness of the algorithm.

Table 2- Overview of research methodology

Methodology stage	Description
Data collection	Use a publicly available soccer video dataset with annotated head injuries
Preprocessing	Use the Time Shift Module (TSM) to preprocess input frames and extract spatio-temporal features from video data.
Feature learning	Use the ResNet-50 architecture for feature learning and classification of head injuries
Education	Model training using RMSprop optimizer and binary cross-entropy loss function for 10 cycles
Evaluating	The performance of the model in a test set containing 500 football videos using the criteria of accuracy, recall and F1 score.

Intervention Protocols

The intervention protocol involves applying a deep learning model to analyze soccer videos for head injury detection. The process starts with collecting a dataset of soccer videos, which are annotated to indicate instances of head injuries. This dataset is crucial for training, validating, and testing the algorithm's effectiveness in identifying head injuries from video footage.

Through this intervention, the study aims to leverage advanced machine learning techniques for enhancing sports safety by providing a tool that can automatically detect potential head injuries in real-time or from recorded video data.

Data Collection

The data collection for this study involves sourcing a publicly accessible dataset of 2000 soccer videos, annotated for head injuries, totaling 50 hours of gameplay. These high-definition videos (1920x1080 pixels) at 30 frames per second include both instances of head injuries (positive examples) and non-injury events (negative examples), providing a comprehensive basis for training and testing the deep learning model aimed at identifying head injuries. This dataset's extensive and annotated nature is pivotal for developing an accurate and reliable injury detection algorithm.

Preprocessing and Feature Extraction

The preprocessing and feature extraction process involves the application of the Time Shift Module (TSM) to video data, adjusting input frames to optimize spatio-temporal feature extraction. This crucial step prepares the data for deep learning analysis, enhancing the model's ability to discern patterns indicative of head injuries. By leveraging both spatial and temporal information within the video frames, TSM facilitates the extraction of meaningful features that significantly contribute to the accuracy and reliability of the head injury detection algorithm.

Model Training and Feature Learning

The model training and feature learning phase utilizes the ResNet-50 architecture, a deep convolutional network pre-trained on the ImageNet dataset to leverage existing knowledge for quicker learning. This phase involves enhancing ResNet-50 with additional dense and classification layers for binary classification of head injuries. The model undergoes 10 training cycles with both training and validation datasets, employing the RMSprop optimizer and binary cross-entropy loss function to optimize for accuracy and ensure the model's capability to generalize well to unseen data.

Test Procedures

The testing phase involves evaluating the trained model's performance on a separate test set comprising 500 football videos not seen by the model during training. This evaluation uses metrics such as accuracy, precision, recall, and the F1 score to assess the model's ability to accurately and reliably identify head injuries. The choice of these metrics provides a comprehensive understanding of the model's performance, highlighting its strengths and areas for improvement.

Performance Evaluation

The performance of the algorithm was evaluated on a validation dataset using standard evaluation criteria. The evaluation criteria used were: precision, accuracy, and F1 score

Accuracy: (TP + TN) / (TP + TN + FP + FN)

Precision: TP / (TP + FP) Recall: TP / (TP + FN)

F^1-score: 2 * (precision * recall) / (precision + recall)

where TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives, and FN is the number of false negatives.

The performance evaluation detailed uses standard metrics: accuracy, precision, recall, and F1 score, for assessing the algorithm on a test set of 500 football videos. With an overall accuracy of 0.986, the model shows high effectiveness in classifying head injuries correctly. The precision (0.89), recall (0.97), and F1 score (0.93) further indicate the model's balanced capability in minimizing false positives and false negatives, showcasing its reliability and precision in detecting head impact events from video data. This comprehensive evaluation underscores the algorithm's potential in real-world applications for monitoring and preventing head injuries in sports.

Results and Discussion

The primary objective of this study was to develop a novel deep learning approach for detecting head injuries in soccer videos by leveraging spatio-temporal features. Employing a combination of Time Shift Module (TSM) for input frame preprocessing and ResNet-50 architecture for feature learning and classification, our model demonstrated outstanding performance on a test set of 500 soccer videos. It achieved an overall accuracy of 0.986, marking a substantial improvement over previous research efforts in sports safety and injury detection.

In contrast to earlier studies that predominantly relied on direct kinematic data from wearable sensors or finite element (FE) simulations, our approach introduces a non-invasive, scalable, and potentially more accurate method. Earlier attempts at detecting head injuries in sports have primarily depended on kinematic data from wearable sensors or FE simulations. These methods, while insightful, are encumbered by several limitations including high implementation costs, data inaccuracies, and the intrinsic limitations of sensor-based or simulation models (Patton et al., 2020; Sigmond et al., 2016). Our video analysis, by contrast, provides a comprehensive view of the game, capturing every visible impact without the necessity for physical instrumentation on players. This method not only addresses the limitations associated with sensor-based or FE simulation methodologies but also significantly enhances the accuracy and reliability of head injury detection in soccer. The integration of TSM has proven crucial in capturing the temporal dynamics of soccer play, which are often missed by sensor-based methods. This feature allows our model to detect subtle yet potentially injurious head impacts that might not meet the thresholds set by sensor-based systems. Additionally, the use of ResNet-50 for feature extraction and classification capitalizes on the strengths of deep learning to identify complex patterns within the data, offering a nuanced analysis beyond what is achievable through traditional manual video review methods or straightforward kinematic data analysis.

Conclusion

The study presented a novel deep learning model for detecting head injuries in soccer videos with high accuracy, leveraging spatio-temporal features. By achieving an accuracy of 0.986, the model demonstrates significant potential for application in sports and medical monitoring systems, offering an efficient tool for real-time head injury detection. This approach not only surpasses the performance of existing methods but also opens new avenues for extending similar technologies to other sports and medical contexts where head injury detection is crucial. The successful implementation of this model could revolutionize the way head injuries are monitored and managed, contributing to improved safety and health outcomes for athletes and patients alike. Further research and development are encouraged to refine the model, expand its applicability, and integrate it into practical, real-world applications.

Strengths of the Study

1. Advanced Computational Techniques: By leveraging state-of-the-art deep learning libraries and frameworks, such as TensorFlow or PyTorch, along with the ResNet-50 architecture, the study utilizes the forefront of technology to analyze complex video data. This ensures a high level of accuracy and generalizability in detecting head impacts, surpassing the capabilities of traditional methods.
2. Non-Invasive Detection: Unlike methods that require wearable sensors, this video analysis approach is non-invasive. It eliminates the need for any physical device to be worn by players, thereby avoiding potential discomfort and compliance issues, and allows for the uninterrupted monitoring of all players simultaneously.

3. Scalability and Efficiency: The deep learning model offers a scalable solution that can be applied to vast datasets, such as video footage from an entire football season. This scalability, combined with the efficiency of the algorithm, facilitates the rapid and accurate detection of head impacts across numerous games and leagues.
4. Enhanced Player Safety: By enabling the early detection of head injuries, the research contributes to the reduction of long-term damage and improves recovery outcomes. This proactive approach to injury management represents a significant advancement in protecting athletes and ensuring their long-term health and well-being.

Practical Implications

1. Real-Time Monitoring and Intervention: The study's methodology could be implemented in real-time monitoring systems, allowing medical teams to immediately identify potential head injuries during matches. This timely intervention can lead to quicker assessments and treatments, potentially mitigating the severity of injuries.
2. Policy and Protocol Development: The findings from this research can inform the development of new safety protocols and policies within sports organizations. By providing empirical evidence of the effectiveness of video analysis in injury detection, sports leagues may adopt similar technologies to prioritize athlete health.
3. Training and Prevention Programs: Coaches and trainers can use insights from the deep learning model to understand the circumstances under which head impacts occur most frequently. This information can guide the design of training programs aiming at reducing the risk of head injuries.
4. Broader Application Across Sports: While focusing on football, the principles and methodologies of this study can be adapted to other sports where head injuries are a concern. This broad applicability underscores the potential of deep learning to transform injury prevention strategies across the sporting world.

In conclusion, this research embodies a pivotal shift towards integrating advanced technological solutions in sports safety. The strength of the study lies in its innovative use of deep learning to address a critical health issue, while its practical implications extend far beyond football, offering a model for enhancing athlete safety across various sports disciplines.

Limitations

While the model shows promising results, its dependency on video quality and angle poses potential limitations. The accuracy of head injury detection could be compromised by factors such as poor lighting, obstructions, or low-resolution footage. This challenge, although not unique to this study, underscores the need for high-quality video in diverse playing environments and levels.

In comparison, sensor-based studies face different challenges, including user compliance and sensor calibration issues, but do not directly contend with the variability of video quality. This highlights a trade-off between the broader applicability of video analysis and the controlled precision of sensor data.

The adoption of a deep learning approach to detect head injuries in football, utilizing spatial-temporal features from video data, represents a significant leap forward in sports medicine and player safety. This study not only addresses the urgent need for improved head injury detection methods but also sets a new benchmark in the application of technology to enhance health outcomes in sports. The strengths and practical implications of this research are manifold, offering a comprehensive solution to a longstanding challenge in the field. Moreover, the generalizability of the proposed model across different soccer play levels and environments has yet to be fully established. The varying dynamics of play between amateur and professional levels may affect the model's detection capabilities, suggesting the need for broader validation to ensure its efficacy across all levels of play.

Future Directions

To enhance the model's robustness and accuracy, future research should explore multi-angle video analysis. This could mitigate the limitations associated with single-angle footage and improve the model's comprehensiveness in capturing head impacts. Additionally, evaluating the model's performance in diverse conditions and across various levels of soccer play will provide valuable insights into its adaptability and utility in real-world scenarios.

Ethical considerations

Ethical considerations need to be taken into account when developing methods for detecting head injuries in football. The safety and well-being of the players must be a top priority, and this should reflect in the data collection and analysis methods. The collection of data should not jeopardize the privacy or dignity of the players, and informed consent should be obtained from all participants.

Furthermore, there is a risk that the proposed algorithm could be used to unfairly penalize players who have suffered head injuries, leading to discrimination and negative consequences for their careers. It is important to recognize that the algorithm is only a tool to aid in the detection and management of head injuries and should not be used as a sole determinant of a player's abilities or value.

In addition, the algorithm should not be used to replace medical professionals' assessments or decisions. The algorithm provides important information, but medical professionals should always be involved in the diagnosis and treatment of head injuries in football.

Overall, ethical considerations should be taken into account when developing and using the proposed algorithm. The safety, privacy, and well-being of the players should be a top priority, and the algorithm should be used judiciously alongside proper medical evaluation and care.

Compliance with Research Ethics Guidelines

This study was conducted with compliance with research ethics guidelines. The publicly available soccer video dataset used for the study was ethically sourced and all relevant ethical concerns were addressed during the data collection process. Informed consent was not required as the videos were already available in the public domain. The study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki and the International Council of Medical Journal Editors (ICMJE) guidelines. The study was approved by the relevant institutional review board (IRB) and complied with all applicable laws and regulations. Data privacy and confidentiality were maintained throughout the study and any personal identifying information in the dataset remained anonymous to protect the privacy of the players. The results of this study may have important implications for player safety and injury prevention in sports, and this research should continue to be conducted with the utmost adherence to ethical guidelines.

Authors' Contributions

The author of this study has adopted a deep learning approach to detect head injuries in football video data using spatial-temporal features. The proposed method employs the ResNet-50 architecture and the Temporal Shift Module (TSM) for feature learning and classification, resulting in high accuracy in detecting head impact events. The author also evaluated the algorithm on a test set containing 500 soccer videos and achieved an overall accuracy of 0.986. The research provides promising implications for the sports and medical industries, allowing for real-time monitoring and treatment of head injuries.

Conflict of interest

The author declares no conflict of interest in this study.

Acknowledgment

I would like to express my gratitude to the creators and curators of the publicly available soccer video datasets used in this study. This research would not have been possible without their efforts. I would also like to acknowledge the valuable support and guidance provided by the professors of Computer Science and Sports Management as well as respected mentors throughout the research process. Finally, I sincerely thank the programmers who spent their time and effort to make this research possible.

References

1. Allison, M. A., Kang, Y. S., Bolte, J. H., Maltese, M. R., & Arbogast, K. B. (2014). Validation of a helmet-based system to measure head impact biomechanics in ice hockey. *Medicine and science in sports and exercise*, *46*(1), 115-123.
2. Beaudouin, F., Demmerle, D., Fuhr, C., Tröß, T., & Meyer, T. (2021). Head impact situations in professional football (soccer). *Sports medicine international open*, *5*(02), E37-E44.
3. Beckwith, J. G., Greenwald, R. M., Chu, J. J., Crisco, J. J., Rowson, S., Duma, S. M., ... & Collins, M. W. (2013). Head impact exposure sustained by football players on days of diagnosed concussion. *Medicine and science in sports and exercise*, *45*(4), 737.
4. Bewley, A., Ge, Z., Ott, L., Ramos, F., & Upcroft, B. (2016, September). Simple online and realtime tracking. In *2016 IEEE international conference on image processing (ICIP)* (pp. 3464-3468). IEEE.
5. Bourdet, N., Deck, C., Trog, A., Meyer, F., Noblet, V., & Willinger, R. (2021, September). Deep learning methods applied to the assessment of brain injury risk. In Proceedings of International Research Conference on the Biomechanics of Impacts.
6. Caccese, J. B., Lamond, L. C., Buckley, T. A., & Kaminski, T. W. (2016). Reducing purposeful headers from goal kicks and punts may reduce cumulative exposure to head acceleration. *Research in sports medicine*, *24*(4), 407-415.
7. Campbell, K. R., Marshall, S. W., Luck, J. F., Pinton, G. F., Stitzel, J. D., Boone, J. S., ... & Mihalik, J. P. (2020). Head impact telemetry system's video-based impact detection and location accuracy. *Medicine and science in sports and exercise*, *52*(10), 2198.
8. Chrisman, S. P., Ebel, B. E., Stein, E., Lowry, S. J., & Rivara, F. P. (2019). Head impact exposure in youth soccer and variation by age and sex. *Clinical journal of sport medicine*, *29*(1), 3-10.
9. Deliege, A., Cioppa, A., Giancola, S., Seikavandi, M. J., Dueholm, J. V., Nasrollahi, K., ... & Van Droogenbroeck, M. (2021). Soccernet-v2: A dataset and benchmarks for holistic understanding of broadcast soccer videos. In *Proceedings of the*

IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 4508-4519).
10. Donahue, J., Anne Hendricks, L., Guadarrama, S., Rohrbach, M., Venugopalan, S., Saenko, K., & Darrell, T. (2015). Long-term recurrent convolutional networks for visual recognition and description. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 2625-2634).
11. Fafula, A., & Peterson, R. (2015). Predicting Global Economic Activity with Media Analytics. *Available on Research Gate*.
12. Fanton, M., Wu, L., & Camarillo, D. (2020). Comment on "Frequency and magnitude of game-related head impacts in male contact sports athletes: a systematic review and meta-analysis". *Sports medicine*, *50*(4), 841-842.
13. Forsyth, D., & Ponce, J. (2012). Computer vision: A modern approach. Always learning.
14. Gabler, L. F., Huddleston, S. H., Dau, N. Z., Lessley, D. J., Arbogast, K. B., Thompson, X., ... & Crandall, J. R. (2020). On-field performance of an instrumented mouthguard for detecting head impacts in American football. Annals of biomedical engineering, 48, 2599-2612.
15. Ghazi, K., Wu, S., Zhao, W., & Ji, S. (2021). Instantaneous whole-brain strain estimation in dynamic head impact. Journal of Neurotrauma, 38(8), 1023-1035.
16. Jiang, Y., Cui, K., Chen, L., Wang, C., & Xu, C. (2020, October). Soccerdb: A large-scale database for comprehensive video understanding. In *Proceedings of the 3rd International Workshop on Multimedia Content Analysis in Sports* (pp. 1-8).
17. Jocher, G., Stoken, A., Borovec, J., Chaurasia, A., Changyu, L., Laughing, A. V., ... & Ingham, F. (2021). ultralytics/yolov5: v5. 0-YOLOv5-P6 1280 models AWS Supervise. ly and YouTube integrations. *Zenodo*, *11*.
18. King, D., Hume, P., Gissane, C., Brughelli, M., & Clark, T. (2016). The influence of head impact threshold for reporting data in contact and collision sports: systematic review and original data analysis. *Sports medicine*, *46*(2), 151-169.
19. Kuo, C., Wu, L., Loza, J., Senif, D., Anderson, S. C., & Camarillo, D. B. (2018). Comparison of video-based and sensor-based head impact exposure. *PloS one*, *13*(6), e0199238.
20. Kontos, A. P., Dolese, A., Elbin Iii, R. J., Covassin, T., & Warren, B. L. (2011). Relationship of soccer heading to computerized neurocognitive performance and symptoms among female and male youth soccer players. *Brain Injury*, *25*(12), 1234-1241.
21. Karpathy, A., Toderici, G., Shetty, S., Leung, T., Sukthankar, R., & Fei-Fei, L. (2014). Large-scale video classification with convolutional neural networks. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition* (pp. 1725-1732). Karpathy, A., Toderici, G., Shetty, S., Leung, T., Sukthankar, R., & Fei-Fei, L. (2014). Large-scale video classification with convolutional neural networks. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition* (pp. 1725-1732).

22. Gu, Y., Wang, Q., & Qin, X. (2021, October). Real-time streaming perception system for autonomous driving. In *2021 China Automation Congress (CAC)* (pp. 5239-5244). IEEE.
23. Li, Z., Gavrilyuk, K., Gavves, E., Jain, M., & Snoek, C. G. (2018). Videolstm convolves, attends and flows for action recognition. *Computer Vision and Image Understanding*, *166*, 41-50.
24. Lin, T. Y., Maire, M., Belongie, S., Bourdev, L., Girshick, R., Hays, J., ... & Dollár, P. (2015). Microsoft COCO: common objects in context. arXiv. *arXiv preprint arXiv:1405.0312*, *21*.
25. Lin, J., Gan, C., & Han, S. (2019). Tsm: Temporal shift module for efficient video understanding. In *Proceedings of the IEEE/CVF International Conference on Computer Vision* (pp. 7083-7093).
26. Lipton, M. L., Kim, N., Zimmerman, M. E., Kim, M., Stewart, W. F., Branch, C. A., & Lipton, R. B. (2013). Soccer heading is associated with white matter microstructural and cognitive abnormalities. *Radiology*, *268*(3), 850.
27. Lipton, Z. C., Elkan, C., & Narayanaswamy, B. (2014). Thresholding classifiers to maximize F1 score. *arXiv preprint arXiv:1402.1892*.
28. Hanlon, E. M., & Bir, C. A. (2012). Real-time head acceleration measurement in girls' youth soccer. *Medicine and science in sports and exercise*, *44*(6), 1102-1108.
29. Haran, F. J., Tierney, R., Wright, W. G., Keshner, E., & Silter, M. (2013). Acute changes in postural control after soccer heading. *International journal of sports medicine*, *34*(04), 350-354.
30. Hasija, V., & Takhounts, E. G. (2022). Deep learning methodology for predicting time history of head angular kinematics from simulated crash videos. Scientific Reports, 12(1), 6526.
31. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).
32. Martin, Z., Hendricks, S., & Patel, A. (2021). Automated tackle injury risk assessment in contact-based sports-a rugby union example. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 4594-4603).
33. Miller, L. E., Pinkerton, E. K., Fabian, K. C., Wu, L. C., Espeland, M. A., Lamond, L. C., ... & Urban, J. E. (2020). Characterizing head impact exposure in youth female soccer with a custom-instrumented mouthpiece. *Research in Sports Medicine*, *28*(1), 55-71.
34. Montenigro, P. H., Alosco, M. L., Martin, B. M., Daneshvar, D. H., Mez, J., Chaisson, C. E., ... & Tripodis, Y. (2017). Cumulative head impact exposure predicts later-life depression, apathy, executive dysfunction, and cognitive impairment in former high school and college football players. *Journal of neurotrauma*, *34*(2), 328-340.

35. Nevins, D., Hildenbrand, K., Kensrud, J., Vasavada, A., & Smith, L. (2016). Field evaluation of a small form-factor head impact sensor for use in soccer. *Procedia engineering*, *147*, 186-190.
36. O'Connor, K. L., Rowson, S., Duma, S. M., & Broglio, S. P. (2017). Head-impact–measurement devices: a systematic review. *Journal of athletic training*, *52*(3), 206-227.
37. Patton, D. A., Huber, C. M., Jain, D., Myers, R. K., McDonald, C. C., Margulies, S. S., ... & Arbogast, K. B. (2020). Head impact sensor studies in sports: a systematic review of exposure confirmation methods. *Annals of biomedical engineering*, *48*(11), 2497-2507.
38. Press, J. N., & Rowson, S. (2017). Quantifying head impact exposure in collegiate women's soccer. *Clinical journal of sport medicine*, *27*(2), 104-110.
39. Raymond, S. J., Cecchi, N. J., Alizadeh, H. V., Callan, A. A., Rice, E., Liu, Y., ... & Camarillo, D. B. (2022). Physics-informed machine learning improves detection of head impacts. Annals of biomedical engineering, 50(11), 1534-1545.
40. Rezaei, A., & Wu, L. C. (2022). Automated soccer head impact exposure tracking using video and deep learning. *Scientific reports*, *12*(1), 9282.
41. Rico-González, M., Pino-Ortega, J., Méndez, A., Clemente, F., & Baca, A. (2023). Machine learning application in soccer: a systematic review. Biology of sport, 40(1), 249-263.
42. Rodrigues, A. C., Lasmar, R. P., & Caramelli, P. (2016). Effects of soccer heading on brain structure and function. *Frontiers in neurology*, *7*, 38.
43. Sanchez, E. J., Gabler, L. F., Good, A. B., Funk, J. R., Crandall, J. R., & Panzer, M. B. (2019). A reanalysis of football impact reconstructions for head kinematics and finite element modeling. Clinical biomechanics, 64, 82-89.
44. Sandmo, S. B., Gooijers, J., Seer, C., Kaufmann, D., Bahr, R., Pasternak, O., ... & Koerte, I. K. (2021). Evaluating the validity of self-report as a method for quantifying heading exposure in male youth soccer. *Research in sports medicine*, *29*(5), 427-439.
45. Siegmund, G. P., Guskiewicz, K. M., Marshall, S. W., DeMarco, A. L., & Bonin, S. J. (2016). Laboratory validation of two wearable sensor systems for measuring head impact severity in football players. *Annals of biomedical engineering*, *44*(4), 1257-1274.
46. Stemper, B. D., Shah, A. S., Harezlak, J., Rowson, S., Mihalik, J. P., Duma, S. M., ... & CARE Consortium Investigators. (2019). Comparison of head impact exposure between concussed football athletes and matched controls: evidence for a possible second mechanism of sport-related concussion. *Annals of biomedical engineering*, *47*, 2057-2072.
47. Stewart, W. F., Kim, N., Ifrah, C. S., Lipton, R. B., Bachrach, T. A., Zimmerman, M. E., ... & Lipton, M. L. (2017). Symptoms from repeated intentional and unintentional head impact in soccer players. *Neurology*, *88*(9), 901-908.

48. Stephens, R., Rutherford, A., Potter, D., & Fernie, G. (2010). Neuropsychological consequence of soccer play in adolescent UK school team soccer players. *The Journal of neuropsychiatry and clinical neurosciences*, *22*(3), 295-303.
49. Takhounts, E. G., Eppinger, R. H., Campbell, J. Q., Tannous, R. E., Power, E. D., & Shook, L. S. (2003). On the development of the SIMon finite element head model (No. 2003-22-0007). SAE Technical Paper.
50. Thomas, G., Gade, R., Moeslund, T. B., Carr, P., & Hilton, A. (2017). Computer vision for sports: Current applications and research topics. *Computer Vision and Image Understanding*, *159*, 3-18.
51. Wang, T., Kenny, R., & Wu, L. C. (2021). Head impact sensor triggering bias introduced by linear acceleration thresholding. *Annals of biomedical engineering*, *49*(12), 3189-3199.
52. Wang, X., & Gupta, A. (2018). Videos as space-time region graphs. In *Proceedings of the European conference on computer vision (ECCV)* (pp. 399-417).
53. Wu, S., Zhao, W., Ghazi, K., & Ji, S. (2019). Convolutional neural network for efficient estimation of regional brain strains. Scientific reports, 9(1), 17326.
54. Wu, L. C., Nangia, V., Bui, K., Hammoor, B., Kurt, M., Hernandez, F., ... & Camarillo, D. B. (2016). In vivo evaluation of wearable head impact sensors. *Annals of biomedical engineering*, *44*(4), 1234-1245.
55. Yue-Hei Ng, J., Hausknecht, M., Vijayanarasimhan, S., Vinyals, O., Monga, R., & Toderici, G. (2015). Beyond short snippets: Deep networks for video classification. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 4694-4702).
56. Zhan, X., Liu, Y., Raymond, S. J., Alizadeh, H. V., Domel, A. G., Gevaert, O., ... & Camarillo, D. B. (2020). Deep learning head model for real-time estimation of entire brain deformation in concussion. arXiv preprint arXiv:2010.08527.
57. Zhan, X., Liu, Y., Raymond, S. J., Alizadeh, H. V., Domel, A. G., Gevaert, O., ... & Camarillo, D. B. (2021). Rapid estimation of entire brain strain using deep learning models. IEEE Transactions on Biomedical Engineering, 68(11), 3424-3434.
58. Zhuang, F., Qi, Z., Duan, K., Xi, D., Zhu, Y., Zhu, H., ... & He, Q. (2020). A comprehensive survey on transfer learning. *Proceedings of the IEEE*, *109*(1), 43-76.