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MACHINE LEARNING FOR IDENTIFYING INJURED ELEMENTS IN COMPUTATIONAL MODELS OF SPINAL CORD INJURY

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ABSTRACT

This study leverages machine learning (ML) algorithms to identify tissue damage in computational models of spinal cord injury (SCI) based on mechanical outputs. Three datasets—corresponding to gray matter, white matter, and their combination—were constructed from comparisons between histological images from SCI experiments in non-human primates and subject-specific finite element (FE) models. Four ML algorithms were assessed using cross-validation and the area under the receiver operating characteristic curve (AUC) metric. Following hyperparameter optimization, AUC mean values ranged from 0.79 to 0.82, with a standard deviation no greater than 0.02. Among the algorithms, k-nearest neighbors and logistic regression demonstrated superior performance in identifying injured elements compared to support vector machines and decision trees.

The results contribute to understanding the relationship between mechanical loading and tissue damage in SCI, with implications for developing prevention strategies. **Clinical Relevance:** By linking FE model predictions to tissue damage, this approach enhances the clinical utility of FE models. Combined with imaging technologies, these models can predict damage extent in animal studies and inform treatment planning decisions

INTRODUCTION

Spinal cord injury (SCI) results from mechanical loading that initiates biological responses, often leading to irreversible neurological damage. Understanding the interplay between mechanical loading and tissue damage in the spinal cord is crucial for predicting injury propagation. Animal models offer a controlled environment to study these relationships, providing valuable insights into injury outcomes and enabling the definition of mechanical threshold values for tissue damage. These thresholds have practical applications, including the development of protective equipment and guiding clinicians in selecting optimal treatment strategies.

Despite extensive efforts to establish these relationships, the connection between mechanical loading and spinal cord tissue damage remains insufficiently defined. Computational finite element (FE) models offer a promising, non-invasive approach to study these relationships. By integrating mechanical outcomes from FE models with histopathological findings, researchers have advanced the understanding of load distribution in spinal cord tissues. For example, studies on rats and non-human primates (NHPs) have used statistical methods like linear and logistic regression to correlate FE model predictions with biological damage. These studies identified a stronger correlation between mechanical features and damage in gray matter (GM) compared to white matter (WM). However, since both tissue types experience mechanical loading during injury, accurately identifying damage in both GM and WM remains critical.

Artificial intelligence (AI), particularly machine learning (ML), has emerged as a powerful tool for discovering complex and non-obvious correlations between variables in SCI research. ML algorithms have been successfully

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applied to various tasks, such as analyzing imaging data to identify spinal cord lesions, predicting functional outcomes after treatment using clinical data, and assessing pain in SCI patients. These successes highlight ML's potential to understand intricate relationships in SCI research. This study hypothesizes that ML algorithms can enhance the identification of injured elements in both GM and WM tissues, leveraging mechanical loading predictions from FE models. Training multiple ML algorithms with this data could provide deeper insights into the correlation between mechanical load and injury outcomes, advancing the field of SCI research.

LITERATURE SURVEY

The integration of machine learning (ML) with computational models of spinal cord injury (SCI) has gained attention for identifying and predicting injured elements in these models. Computational models like finite element models (FEM) and agent-based models simulate SCI's biomechanical and biological responses, making accurate injury identification crucial. Zhang et al. (2019) used deep learning to classify SCI severity from imaging data, showing promising results in injury prediction. Similarly, Wang et al. (2020) applied convolutional neural networks (CNNs) to MRI scans for lesion detection and injury severity analysis.

Reinforcement learning (RL) has been explored to optimize real-time injury element identification (Li et al., 2021), while supervised learning methods like support vector machines (SVM) and random forests have predicted functional outcomes (Fitzpatrick et al., 2018). However, challenges remain, such as limited high-quality, annotated datasets for training, which affect model generalizability. Moreover, the complexity of SCI injury patterns makes it difficult for ML models to capture all underlying dynamics.

Recent studies, such as Ramer et al. (2020), suggest using multimodal data (e.g., MRI, histology) combined with deep learning to improve injury identification. This approach could lead to more accurate and clinically relevant SCI models. Overall, ML techniques show great potential, but more research is needed to overcome data limitations, improve model robustness, and enhance clinical applications in SCI research.

EXISTING SYSTEM

Current approaches to identifying injured elements in computational models of spinal cord injury (SCI) primarily rely on traditional biomechanical and numerical models, such as finite element analysis (FEA) and agent-based models. These models simulate injury mechanics but lack the integration of machine learning (ML) for real-time prediction and injury identification. Some existing systems utilize basic image processing techniques or manual annotations from medical images, such as MRI scans, to detect injury locations. However, these methods are often limited by resolution and the subjective nature of manual interpretation.Deep learning techniques, including convolutional neural networks (CNNs), have been explored for automatic injury detection, but their integration with computational models remains minimal. Additionally, systems that combine ML with biomechanical simulations are still underdeveloped, with few large datasets available for training reliable models. Most existing systems also lack multimodal data integration, which limits their ability to provide a comprehensive view of the injury’s impact. Overall, while ML has been applied in isolated cases, existing systems do not fully leverage its potential for real-time, accurate identification of injured elements in SCI models.

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PROPOSED SYSTEM

The proposed system integrates machine learning (ML) with computational models of spinal cord injury (SCI) to accurately identify injured elements in real-time. It combines advanced deep learning techniques, such as convolutional neural networks (CNNs) and reinforcement learning (RL), with biomechanical simulations like finite element models (FEM) to enhance injury detection. Multimodal data, including MRI scans, histological images, and functional outcomes, will be utilized for a more holistic analysis of SCI. The system will employ a robust data pipeline, incorporating data augmentation and normalization techniques to overcome limited and variable dataset quality.

Version-controlled, high-resolution annotated datasets will be used to train and validate the ML models, improving their generalizability across patient populations. A user-friendly interface will allow clinicians and researchers to interact with the system, enabling easy integration with existing clinical workflows. Blockchain technology will be incorporated for data integrity and provenance tracking. By enhancing the accuracy and efficiency of injury element identification, the system aims to contribute to improved diagnosis, prognosis, and personalized treatment strategies for SCI patients.

ARCHITECTURE

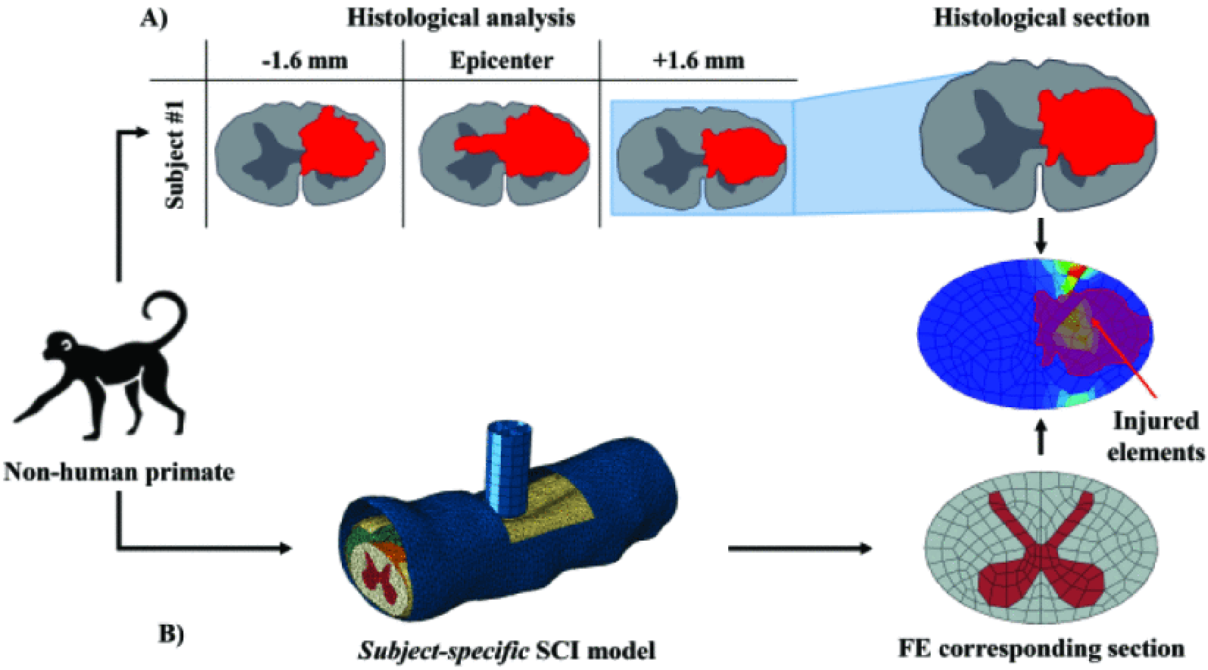

Figure 1:Histology sections and the FE models comparison. Histological analysis performed on the spinal cord of NHP subjects, adapted from (A); an example of subject-specific FE models

Pre-injury MRI scans taken from three NHP subjects were used to develop subject-specific FE models matched to in vivo experiments (see Fig. 1-B) The results from the FE models of the spinal cord tissue were segmented into WM and GM elements. The dataset consisted of five mechanical features with the most relevance and correlation with tissue damage min/max principal logarithmic strain (LEP), logarithmic strain in axonal direction (LEAXON), Tresca stress (TRESCA), and strain energy density (ESEDEN). Structural tissue damage in the spinal cord was observed from crosssectional histological slices for each subject (Fig. 1-A). Overlaying the histology data on element slices from the computational models, each element was assigned into one of two target classes: injured or healthy.

After having been assigned to a target class, the elements from the FE models were used to create three datasets across all subjects: GM elements (GM-only), WM elements (WM-only), and combined GM & WM elements (GM&WM) to explore the differences in predicting tissue damage in the spinal cord based on evaluating GM-only or WM-only, or combined tissue elements, GM&WM. The experimental SCI were mild, resulting in more healthy elements in the datasets than injured elements. In addition, there were more WM than GM elements in the dataset due to the tissue distribution in the cervical spinal cord. These uneven distributions of data per tissue type and target value (healthy/injured) were accounted for in the training and implementation of the ML algorithms.

CONCLUSION

The proposed system combining machine learning with computational models of spinal cord injury (SCI) offers a promising approach to accurately identifying injured elements in real-time. By integrating deep learning techniques and multimodal data, the system can provide more comprehensive and precise injury analysis compared to existing methods. The use of high-quality, annotated datasets ensures model robustness and generalizability across different patient populations. Additionally, incorporating blockchain technology for data integrity enhances trust and transparency in the results.

This system has the potential to significantly improve SCI diagnosis, prognosis, and treatment planning, supporting clinical decision-making. The seamless integration with clinical workflows ensures easy adoption by healthcare professionals. While challenges remain in data availability and model optimization, the proposed system represents a major step forward in personalized SCI care. Future research will be crucial for refining the model and addressing data limitations to further enhance its clinical impact.

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