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Explainable AI Based Neck Direction Prediction and Analysis Using Yolov8

Y. Chitty, Dr. Geeta Tripathi
PG Scholar, Department of Science & Engineering, Guru Nanak Institutions Technical Campus Hyderabad.
Professor & HOD Department of CSE, Guru Nanak Institutions Technical Campus Hyderabad.
chittyjosh002@gmail.com hodcse1.gnitc@gniindia.org

Abstract: The research focuses on using the YOLOv8 model to detect and analyze neck rotation following head collisions in order to propose preventive healthcare treatments. The location and orientation of the neck must be measured and monitored in order to predict its trajectory during such impacts. The experiment, which replicates movements like flexion and lateral rotation based on American football scenarios and simulates minor head hits, will involve ten volunteers—five male and five female. The research focuses on using the YOLOv8 model to detect and analyze neck rotation following head collisions in order to propose preventive healthcare treatments. The location and orientation of the neck must be measured and monitored in order to predict its trajectory during such impacts. The experiment, which replicates movements like flexion and lateral rotation based on American football scenarios and simulates minor head hits, will involve ten volunteers—five male and five female.
Keywords: Yolov8, Trajectory, Flexion.

INTRODUCTION

The musculoskeletal system of the human body facilitates movement and provides support, style, and structure. The muscles of the head and neck control vital functions such as swallowing, chewing, facial expressions, eye movement, and head and neck movement. Musculoskeletal models are efficient computer simulation methods that enable a physically precise analysis of human movement. They are able to provide meta data on joint contact forces, musculotendon lengths, and muscle forces. They support sports performance analysis, neuromuscular coordination research, and musculoskeletal load estimations. The models are used to estimate joint, muscle, and ligament forces that are difficult or impossible to measure experimentally. Open Sim is a free tool developed at Stanford University that allows users to make dynamics simulations of musculoskeletal models for analysis and visualization. Open Sim is a dependable and expandable tool for human motion study because of its integrated feature extraction capabilities and community contributions. Once a musculoskeletal model has been developed, Open Sim makes it easier to analyze how joint kinematics, muscle-tendon characteristics, and musculoskeletal architecture affect forces and typical movements. The Open Sim tool offers additional details on muscle activation and facilitates the modeling of kinetic and kinematic joint characteristics. Inertial measurement units (IMU) are used to collect kinematic data, or information about the movement of bodily components. Conversely, kinetic data provides information on the force exerted by the moving component and aids in the analysis of muscle activity related to the moving joint. This work aims to employ machine learning models for analyzing and identifying the different positions of the human neck in order to prevent and cure musculoskeletal problems in the neck region. Machine learning (ML) is one type of artificial intelligence that is skilled at drawing inferences or forecasts based on data. Deep learning (DL), a type of machine learning, uses multiple-layered artificial neural network activity to define model correctness, fairness, transparency, and AI-driven decision-making outcomes. An organization must be able to explain AI while putting AI models into production if it hopes to gain the respect and confidence of its stakeholders. The main contribution of this work is highlighted as follows: In order to predict the direction of neck movement under load effects, this study analyzed the kinetic data of the neck muscles using both machine learning and basic deep learning techniques. Clinical practitioners can use this research to evaluate the subject's neck muscle status in various neck directions with varying loading effects on the head by giving them genuine explanations for their decisions. The proposed explainable mode might be considered a useful decision support tool for musculoskeletal specialists because it operates more efficiently than its existing counterparts. Enhancing these models' accuracy, efficacy, and applicability for a range of uses, such as clinical decision-making, powered prosthetics, computational pathology, and customized musculoskeletal biomechanics, is the primary objective of research in this field.

OBJECTIVE

The project's objective is to develop a system that uses YOLOv8 to identify and analyze neck rotations during head collisions in order to better understand the risks of head and neck injuries in sports like American football. The research aims to use YOLOv8's advanced object identification capabilities to track the location of the neck in real-time video footage and classify its rotation orientation (flexion, extension, lateral motions) following head impacts. This will provide crucial information regarding the force and direction of neck rotations, which is necessary to assess the danger. In addition to identifying the neck's location, the system will use Explainable AI to provide doctors with understandable data so they can see how the system anticipates neck motions. Integration aims to increase confidence in the model's output, which is important for clinical decision-making. The system will be trained on a wide range of data to ensure that it functions well in a range of scenarios and can generalize to various individuals and head impact types. By monitoring neck motions during head impacts and facilitating quick steps to reduce the possibility of serious injuries, the ultimate goal is to create a dependable, real-time neck rotation prediction system that can promote healthcare preventive.

2.1 PROBLEM STATEMENT

Head and neck injuries are a significant concern in contact sports such as American football, where repeated collisions and impacts can lead to long-term health complications. Monitoring and analyzing neck movements, particularly rotation, flexion, and lateral rotation, is critical for understanding the biomechanical risks associated with these impacts. However, traditional motion analysis methods are either invasive, time-consuming, or lack real-time precision, making them impractical for preventive healthcare applications. There is a need for an accurate, automated, and non-invasive system that can track and analyze neck rotation during collision-like scenarios to predict potential injury risks. This research addresses this gap by utilizing the YOLOv8 deep learning model to detect and monitor neck orientation and trajectory following simulated head collisions, providing a foundation for proposing effective preventive healthcare treatments.

2.2 Existing System

Based on biomechanical data, the XGB (Extreme Gradient Boosting) classifier is used to predict the direction of the neck. One reliable ensemble learning method that is well-known for its effectiveness and performance while working with structured data is the XGB classifier. It functions by constructing a series of decision trees, each of which aims to fix the mistakes produced by the one before it. The model is better able to identify intricate patterns in the dataset—like the tendon force muscle data utilised in this project—thanks to this iterative procedure. With a remarkable 98% accuracy rate, the XGB classifier in the current system proved its capacity to accurately evaluate and forecast the orientation of the neck during head strikes. Notwithstanding its excellent accuracy, the system depends on labelled datasets and offline training and lacks real-time detection capabilities. Although XGB classifiers are helpful for structured data, their usage in dynamic scenarios like real-time neck movement monitoring is limited because they are not inherently able to provide spatial analysis or visual context.

Disadvantage of Existing System

- ➢ It could take longer to train XG Boost than simpler models.
- ➢ Poor generalisation on unknown data may result from over fitting the training data.
- ➢ Without explain ability tools, predictions are hard to understand.

2.3 Proposed System

Neck rotation during head impacts is recognized and examined using the YOLOv8 model. This system tracks the position and direction of the neck in real time using video footage captured during simulated head strikes. These impacts are intended to replicate the flexion and lateral motions present in American football scenarios. The YOLOv8 model, a state-of-the-art object identification model, is trained to precisely identify rotational movements in order to identify and track the location of the neck. By processing video frames, YOLOv8 is able to determine the neck's position during the collision, providing valuable information for predicting the neck's movement. To support clinical decision-making, this technology provides comprehensive, real-time neck rotation predictions and explanations.

Advantages of Proposed System

- ➢ High accuracy in predicting neck movement and direction.
- ➢ Scalable to various types of head impacts and healthcare scenarios.
- ➢ Non-invasive monitoring using video footage, reducing the need for physical sensors.

3. RELATED WORKS

Research on neck direction prediction and analysis continues to evolve as biomechanics, sports science, ergonomics, and machine learning advancements allow us comprehend neck-related problems better. Experts and researchers have been working together to provide efficient methods for injury avoidance, performance improvement, and improved ergonomics.

The authors [16] have analysed Chronic neck pain during single- and dual-task gait using kinematic and kinetic data. The Neighborhood Component Analysis (NCA) and Support Vector Machine algorithm are used to predict with a specificity of 83.30% and sensitivity of 92.85%. Using three wearable sensors during gait, the classification algorithm accurately distinguished between individuals with pain and those without symptoms.

The Random forest algorithm used in [2] achieved 100% accuracy in predictive analysis for detecting human neck postures using a robust integration of kinetics and kinematics. The pros and cons are it serves as a warning system for poor neck posture, but the model's overfitting is not addressed. 31400 K-Nearest Neighbors, Decision Trees, and Random Forest Algorithms are used to predict neck movement data treating neck musculoskeletal disorders using a neckband as a support [17].

In this work [18], for training machine learning algorithms, 28 numerical characteristics were extracted from both the original and transformed shear wave velocity color-coded images, as well as their respective image segments. Six machine learning algorithms were used to perform a supervised binary classification. The random forest algorithm produced the most accurate model for distinguishing elastograms of women with chronic neck pain from asymptomatic women, with an AUC of 0.898.

The authors [14] used a data processing algorithm for motion recognition that provides near real-quantification of head position. Incoming data is filtered, normalized, and divided into data segments. A set of features is extracted from each data segment and employed as input to nine classifiers including Support Vector Machine, Naive Bayes, and KNN for position prediction. A testing accuracy of around 92% was achieved for a set of nine head orientations. The improved prediction performance of ML and logistic regression methods in the current study could be attributed to the potential for greater non linearity between baseline predictors and clinical outcomes.

The benefit of machine learning in prognostic modeling may vary depending on the sample size, variable type, and disease under investigation. The Xgboost algorithm of this work [19] successfully predicted arm pain (AUC = 0.765), neckpain(AUC=0.726), and disability(AUC=0.703)[19]. The existing works advantages and limitations are summarized in Table 1 and hence the problem statement identified.

4. METHODOLOGY OF PROJECT

The proposed methodology for detecting nutrient deficiencies in banana leaves is based on a deep learning framework that leverages convolutional neural networks (CNNs) for automated diagnosis. To begin with, a large dataset of banana leaf images was collected, covering both healthy leaves and those exhibiting symptoms of various nutrient deficiencies such as nitrogen, potassium, and magnesium. Each image was carefully labeled to ensure reliable supervised training of the model.

MODULE DESCRIPTION:

1) Data Collection and Preprocessing: Compile and annotate a dataset of head impact situations, such as pictures or films that depict the posture of the neck during different head impacts (lateral, flexion, and extension).To account for variations in neck movement, make sure the dataset contains both male and female subjects. Make sure the pictures or video frames are pre-processed to be the right size and quality for YOLOv8 input.

2) Model Selection and Configuration: Choose the YOLOv8 model, which has a reputation for detecting objects in real time with speed and accuracy. Depending on the particular needs of neck detection, configure the model architecture and specify parameters like input size, batch size, and learning rate.

3) Labeling and Annotation: Mark the location of the neck and its direction of rotation (flexion, extension, lateral) by annotating the salient characteristics in the video frames or pictures. Label the image's regions of interest (the head and neck) using the proper annotation tools.

4) TrainYOLOv8Model: Train the YOLOv8 model using the labelled dataset. Configure the model according to the right parameters (batch size, input size, etc.).Use the labelled data to train the model, modifying the hyper parameters to maximise efficiency.

5) Test and Evaluate: Test the model's accuracy with unseen photos or video frames after it has been trained. Utilise indicators such as precision and recall to assess the model's performance.

6) Integrate Explainable AI: To make the model's judgements understandable and the outcomes interpretable, use strategies such as class activation maps or saliency maps.

7) Deploy in Real-time: Use live video feeds to include the model into a real-time system that can identify neck rotations after head collisions.

ALGORITHM USED IN PROJECT

This work uses the state-of-the-art object detection model YOLOv8 to detect neck rotation during head collisions. The head and neck areas are designated for training, and the procedure begins with input data in the form of video frames or images that simulate head strikes. Data preprocessing techniques like resizing and normalization are used to ensure consistency and improve model performance. YOLOv8 uses a deep neural network architecture to forecast bounding boxes and class probabilities for items, and it recognizes the head and neck in each frame. During the forward pass, YOLOv8 divides the input into a grid and predicts item positions with extreme accuracy. One post-processing technique for honing the results and getting rid of duplicate detections is Non-Maximum Suppression (NMS). The model operates in real-time, processing frames quickly and continuously, tracking neck movements, and detecting flexion and lateral changes. The forecasts include bounding boxes and confidence scores, and they are used for further study where explainable AI techniques help to clarify the decision-making process. This enables a thorough understanding of how the model detects and interprets neck rotations, offering valuable data for medical applications in monitoring head impacts and preventing mishaps.

6. DATA FLOW DIAGRAM

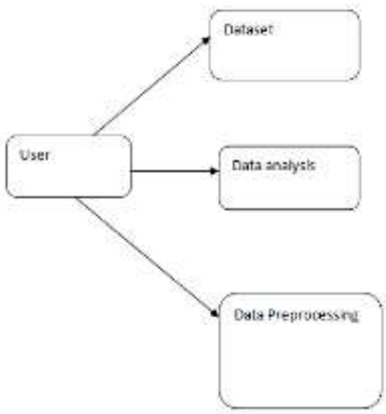
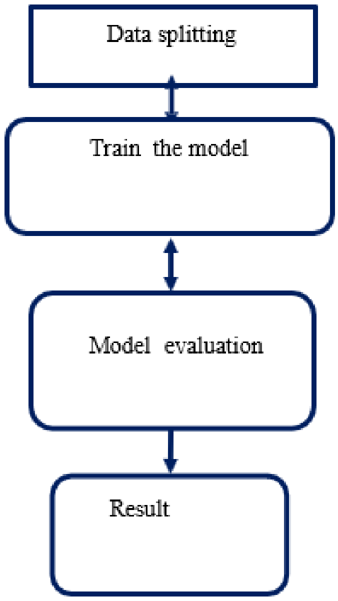


Fig: 6 Flow Diagram



7. SYSTEM ARCHITECTURE

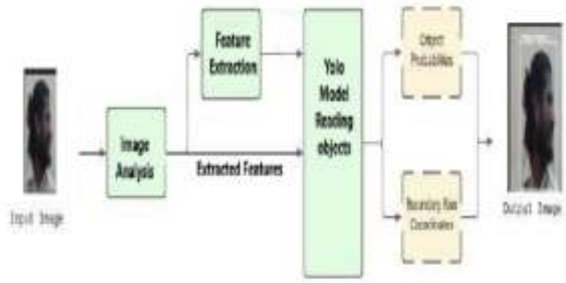


Fig: 7 System Architecture Of Project

8. RESULTS

8.1.1: Homepage

The homepage emphasizes the use of the YOLOv8 object detection model, which enables real-time and precise neck direction detection from images or video streams. YOLOv8 ensures high accuracy and speed for such predictions.

A prominent “Start Here..!” button invites users to explore the project further, suggesting an interactive or demo section where users can engage with the technology or learn more about the system.

8.1.2: About page

The research focuses on detecting and analyzing the neck rotation during head impacts using the YOLOv8 model, with the aim of providing preventive healthcare measures. The neck's position and orientation need to be monitored and measured to predict the direction of the neck during such impacts.

8.1.3: Uploaded image 1

User uploads an image through the web interface.
The AI model (based on YOLOv8) processes the uploaded image to detect the head/neck direction.
The system then presents a comparison view:
i) Original Uploaded Image(left direction)
ii) AI-Predicted Output Image

8.1.5: Uploaded image 3

User uploads an image through the web interface.
The AI model (based on YOLOv8) processes the uploaded image to detect the head/neck direction.
The system then presents a comparison view:
i) Original Uploaded Image(Upwards direction)
ii) AI-Predicted Output Image

8.1.6: Uploaded image 4

User uploads an image through the web interface.
The AI model (based on YOLOv8) processes the uploaded image to detect the head/neck direction.
The system then presents a comparison view:
i) Original Uploaded Image(Downwards direction)
ii) AI-Predicted Output Image

8.1.6: Uploaded image 5

User uploads an image through the web interface.
The AI model (based on YOLOv8) processes the uploaded image to detect the head/neck direction.
The system then presents a comparison view:
i) Original Uploaded Image(Right direction)
ii) AI-Predicted Output Image

8.1.7: Live cam

9. FUTURE ENHANCEMENT

Future advancements in this research could significantly improve its cross-domain application, scalability, and efficacy. Using the YOLOv8 model in real-time systems, such as wearable technologies or motion capture tools, to monitor neck rotations during physical therapy or sports is one potential strategy. Expanding the dataset to include a greater variety of demographics and impact scenarios might increase the model's robustness and generalizability. A more thorough impact assessment may be obtained by integrating multimodal analysis, such as merging data from neck rotation with other physiological measures. By improving the interpretability of forecasts, advanced explain ability techniques can increase clinician trust. Furthermore, the model can be deployed on cloud platforms to facilitate remote monitoring and evaluation, and it can be optimised for edge devices to enable real-time analysis on portable hardware. Additionally, the system can be expanded to cross-domain applications including workplace ergonomics and driving safety monitoring. By adopting these developments, the project can develop into a flexible neck rotation analysis and detection tool that will help the safety, sports, and healthcare sectors.

10. CONCLUSION

The use of YOLOv8 to identify neck rotation during head traumas demonstrates its potential as a useful tool in preventative healthcare. Through precise and efficient neck motion tracking, this gadget ensures that potentially hazardous circumstances during crashes are quickly detected. through the process of corporating. Explainable AI is a technique that ensures transparency and reliability, making it perfect for therapeutic decision-making. This innovative method not only advances biomechanics research but also opens up new avenues for improved patient care and injury prevention in real time.

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