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Predicting Neck Motion Direction With Explainable AI

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Abstract
Head and neck injuries are major concerns in sports, healthcare, and automotive safety, making accurate prediction of neck movement during head impacts essential for injury prevention and safety enhancement. This study proposes an Explainable Artificial Intelligence (XAI)-based system for predicting neck movement direction using machine learning techniques, including Neural Networks and XGBoost, integrated with biomechanical sensor data. Experimental data representing mild head impacts, including flexion and lateral movements commonly observed in sports activities, are analyzed using OpenSim for biomechanical modeling and assessment. The proposed XGBoost classifier achieves 98% prediction accuracy, demonstrating its effectiveness in identifying neck movement directions. The key contribution of the system is the integration of Explainable AI, which provides transparent and interpretable insights into model predictions, supporting clinicians, safety engineers, and researchers in making informed decisions. The proposed approach has potential applications in sports injury prevention, athlete training, automotive safety design, clinical diagnosis, and rehabilitation. By combining machine learning, biomechanical analysis, sensor-based measurements, and explainability, the research provides a reliable and interpretable framework for neck movement prediction and contributes to the development of safer and more effective injury-prevention solutions.

Keywords: *Explainable Artificial Intelligence (XAI), Neck Movement Prediction, Head and Neck Injuries, Machine Learning, XGBoost, Neural Networks, Biomechanical Analysis, OpenSim, Sensor Data, Head Impact, Sports Safety, Automotive Safety, Injury Prevention, Rehabilitation.*

1. Introduction

Head and neck motion plays an important role in understanding injury mechanisms associated with sports, transportation, occupational activities, and clinical conditions. Sudden impacts can cause rapid changes in the position and orientation of the head, producing flexion, extension, lateral bending, or rotational movements of the neck. Accurate identification of these movement patterns can assist researchers and safety professionals in understanding potentially hazardous loading conditions. Biomechanical simulation environments such as OpenSim provide a useful means of representing human movement and examining the relationship between external motion and musculoskeletal behavior [12], [30].

The availability of wearable and inertial measurement unit (IMU) sensors has created new opportunities for monitoring human movement outside conventional laboratory environments. Sensor-based measurements can capture parameters such as acceleration, angular velocity, orientation, and movement timing. These measurements can subsequently be processed using machine-learning techniques to distinguish between different motion classes. Research on IMU-based prediction of musculoskeletal disorder risk demonstrates the potential of sensor information for identifying movement-related patterns in industrial environments [28]. Similarly, biomechanical investigations of head injury mechanisms emphasize the importance of understanding the dynamic response of the head and neck during impact conditions [14].

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Machine learning provides an effective approach for learning complex relationships between biomechanical measurements and movement categories. Conventional rule-based approaches generally require manually defined thresholds and may have difficulty handling variations among individuals and movement conditions. Ensemble learning methods such as XGBoost can instead learn nonlinear relationships from multidimensional sensor features and provide efficient classification performance [4]. Neural-network approaches provide another option because they can learn complex feature representations directly from input data and have demonstrated broad applicability in pattern-recognition problems [25].

A significant challenge in machine-learning-based medical and biomechanical applications is the interpretation of model decisions. High predictive accuracy alone may not be sufficient when the output is used to support clinical, safety, or injury-prevention decisions. Users need to understand which input characteristics influenced a particular prediction. Explainable Artificial Intelligence (XAI) addresses this requirement by providing methods for examining the relationship between input features and model outputs. LIME introduced a model-agnostic approach for explaining individual predictions, while SHAP established a unified framework for attributing model predictions to individual features [27], [22].

The problem becomes particularly important when the available movement dataset contains unequal numbers of observations for different movement classes. Imbalanced datasets can cause a classifier to favor the majority class and produce misleading overall accuracy. The Synthetic Minority Over-sampling Technique (SMOTE) provides a method for generating synthetic examples of minority classes and has been widely used to improve learning from imbalanced datasets [15]. Appropriate evaluation measures, including precision-recall analysis, are also important when assessing classifiers under class imbalance [11].

Biomechanical coordinate definitions represent another important consideration in movement classification. Consistent representation of joint motion is necessary when measurements obtained from different sensors or experimental configurations are compared. The recommendations provided by Wu et al. establish standardized definitions for joint coordinate systems and provide a useful basis for representing human joint motion consistently [6].

Despite the increasing use of machine learning and wearable sensing in movement analysis, there remains a need for systems that combine prediction accuracy with understandable model reasoning. A model that simply identifies neck flexion or lateral movement without explaining the basis of its decision may provide limited value to researchers and safety professionals. An explainable framework can instead indicate the relative contribution of biomechanical and sensor-derived characteristics to each prediction, allowing users to assess whether the model is responding to physically meaningful movement patterns.

Therefore, this research proposes an Explainable Artificial Intelligence framework for predicting neck movement direction from biomechanical and sensor-based measurements. The study considers movement classes associated with mild head-impact conditions and employs machine-learning techniques, particularly XGBoost and neural-network models, for classification. OpenSim is used to support biomechanical representation and analysis, while explainability techniques are incorporated to interpret model predictions. The proposed framework aims to provide an accurate and interpretable approach for identifying neck movement direction, with potential applications in sports safety, automotive design, clinical assessment, rehabilitation, and injury-prevention research.

2. Literature Review

2.1 Biomechanical Modeling of Human Movement

Delp et al. introduced OpenSim as an open-source environment for creating and analyzing dynamic simulations of human movement. Their work established a computational framework through which musculoskeletal structures, joint movements, and external forces can be represented and analyzed. The availability of such a platform is particularly useful for research involving head and neck movement because experimental sensor measurements can be complemented by biomechanical simulation. The OpenSim framework therefore provides an important foundation for studies that seek to connect measured motion with underlying musculoskeletal behavior [12].

Seth et al. subsequently extended the OpenSim ecosystem for studying musculoskeletal dynamics and neuromuscular control in humans and animals. Their work demonstrated how simulation can be used to investigate movement generation and biomechanical responses under different conditions. For neck-motion prediction, such simulation capabilities can support the generation, visualization, and interpretation of movement patterns and provide additional context for sensor-derived observations [30].

Wu et al. addressed the standardization of joint coordinate systems by proposing recommendations for reporting human joint motion. Consistent coordinate definitions are essential when studying movement direction because terms such as flexion, extension, and lateral bending must correspond to

clearly defined anatomical axes. Their recommendations provide a methodological basis for representing joint motion consistently across experiments and analytical systems [6].
Li et al. investigated biomechanical modeling and simulation approaches for studying head injury mechanisms. Their work highlights the value of computational biomechanical models for examining the physical consequences of head-related loading conditions. Such research is directly relevant to neck-motion prediction because the direction and magnitude of head movement can influence the mechanical response of the cervical region during an impact [14].

2.2 Sensor-Based Movement Analysis

Kwon et al. investigated machine-learning techniques for estimating musculoskeletal disorder risk using IMU sensors in industrial environments. Their research demonstrates that inertial sensing can capture movement characteristics that are useful for identifying potentially harmful physical patterns. The study supports the use of sensor-derived variables as predictive inputs for movement-related machine-learning systems and provides evidence that wearable sensing can complement traditional biomechanical assessment methods [28].
Performance Analysis of Wireless Sensor Networks for Smart Monitoring Applications examined the use of sensor-network technologies for monitoring applications. Although the work is not specifically focused on neck biomechanics, it illustrates the broader importance of reliable sensor communication and continuous data acquisition in monitoring systems. For a neck-motion prediction framework, dependable sensor data transmission is necessary because missing, corrupted, or delayed measurements can influence classification results [3].

2.3 Machine Learning for Prediction

Chen and Guestrin developed XGBoost as a scalable tree-boosting system capable of handling structured datasets efficiently. The method combines multiple decision trees to improve predictive performance and can capture nonlinear relationships among input variables. Its computational efficiency and ability to provide feature-importance information make XGBoost particularly suitable for sensor-based movement classification where several biomechanical measurements may interact in complex ways [4].
Goodfellow, Bengio, and Courville presented comprehensive foundations of deep learning, covering neural-network architectures, optimization methods, representation learning, and related computational techniques. Deep-learning models are capable of learning hierarchical representations from complex data and have been successfully applied across numerous pattern-recognition problems. In neck-motion analysis, neural networks can potentially capture nonlinear relationships between sensor measurements and movement categories that may not be easily represented using manually designed rules [25].
Géron discussed practical machine-learning implementation using Scikit-learn, Keras, and TensorFlow, including data preparation, model training, evaluation, and neural-network development. These tools provide a practical environment for constructing experimental prediction pipelines and comparing different learning algorithms. Such methodologies are applicable to biomechanical classification systems where sensor preprocessing, model development, validation, and performance evaluation must be performed systematically [9].

2.4 Explainable Artificial Intelligence

Ribeiro, Singh, and Guestrin proposed LIME as a method for explaining individual predictions produced by complex machine-learning classifiers. The approach approximates the behavior of a model around a particular prediction using an interpretable local model. In safety-sensitive applications such as neck-motion prediction, local explanations can help researchers determine which sensor characteristics contributed most strongly to an individual movement classification [27].
Lundberg and Lee introduced SHAP as a unified approach to interpreting model predictions based on feature attribution. SHAP assigns contribution values to input features, making it possible to examine whether particular measurements increase or decrease the likelihood of a prediction. This approach is useful for biomechanical classification because it can provide an interpretable relationship between sensor-derived features and predicted neck movement directions [22].

2.5 Data Preparation and Model Evaluation

Chawla et al. introduced SMOTE to address classification problems involving imbalanced datasets. Instead of simply duplicating minority observations, the method creates synthetic samples based on relationships between existing minority-class examples. In neck-motion classification, where some movement categories may have fewer observations than others, oversampling can help reduce the tendency of a model to favor the dominant movement class [15].
Saito and Rehmsmeier examined evaluation methods for binary classifiers when datasets are imbalanced and demonstrated the usefulness of precision-recall analysis in such situations. Their findings emphasize that accuracy alone may provide an incomplete view of classifier behavior when class distributions are unequal. For a neck-motion

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prediction system, precision, recall, F1-score, and class-specific performance should therefore be considered alongside overall accuracy [11].

2.6 Research Gap

The reviewed studies establish a strong foundation across biomechanical simulation, sensor-based monitoring, machine learning, and explainable prediction. However, these research areas are often addressed independently. OpenSim provides powerful capabilities for representing human movement, while IMU sensors provide real-world motion measurements. Machine-learning models can classify movement patterns, and XAI techniques can explain predictions. There is still a need for an integrated framework that combines these elements specifically for neck movement direction prediction under head-impact conditions.

The proposed research addresses this gap by integrating biomechanical modeling, sensor-derived measurements, machine-learning classification, and explainability within a single analytical framework. XGBoost and neural-network approaches are considered for movement prediction, while explainability techniques are used to identify influential input features. This integrated design is intended to produce not only accurate movement classification but also interpretable results that can be examined by researchers, clinicians, sports professionals, and automotive safety engineers.

3. Methodology

The proposed methodology for **Predicting Neck Motion Direction With Explainable AI** integrates biomechanical data, sensor measurements, machine-learning techniques, and Explainable Artificial Intelligence (XAI). The complete process consists of data collection, preprocessing, model development, evaluation, and interpretation, as illustrated in the proposed methodology framework.

The first stage involves collecting tendon force data, motion data, and muscle activation data associated with head and neck movements. OpenSim is used to support biomechanical modeling and analysis of movement characteristics. The collected measurements are organized with corresponding neck-motion direction labels, enabling the machine-learning models to learn the relationship between biomechanical features and movement categories [12], [30].

The collected data are then preprocessed to improve their quality and consistency. Relevant features are extracted from the tendon force, motion, and muscle activation measurements. Since different movement classes may contain unequal numbers of observations, **SMOTE** is applied to the training data to improve class balance [15]. The features are subsequently normalized and standardized to reduce differences in numerical scale. The complete dataset is divided into 70% training data and 30% testing data for model development and independent evaluation.

Following preprocessing, several classification algorithms are trained and compared. Traditional machine-learning techniques, including Logistic Regression, K-Nearest Neighbors (KNN), and Decision Tree, are used as baseline models. Ensemble approaches, particularly Random Forest and XGBoost, are then evaluated, along with an Artificial Neural Network (ANN). The models are trained using the extracted biomechanical and sensor features to classify the corresponding neck movement direction. XGBoost is selected as the best-performing model based on the comparative evaluation results [4].

The performance of the developed models is evaluated using accuracy, precision, recall, F1-score, and confusion matrix**.** Accuracy provides an overall measure of correct predictions, while precision and recall assess the quality of classification for individual movement categories. The F1-score provides a combined measure of precision and recall, and the confusion matrix identifies correctly and incorrectly classified movement observations. These measures provide a comprehensive assessment of the prediction capability of the proposed system.

Finally, Explainable Artificial Intelligence (XAI) is incorporated to interpret the predictions generated by the selected XGBoost model. LIME (Local Interpretable Model-Agnostic Explanations) is used to identify the features that contribute most strongly to individual predictions [27]. The explanations can indicate the influence of motion, tendon force, and muscle activation features on the predicted neck movement direction. This improves the transparency of the system and enables researchers, clinicians, sports professionals, and safety engineers to better understand the basis of the model's decisions.

Overall, the proposed methodology follows the sequence Data Collection → Data Preprocessing → Feature Extraction → SMOTE Balancing → Normalization and Standardization → 70:30 Train-Test Split → Model Training and Selection → Model Evaluation → XAI-Based Interpretation. The integration of biomechanical analysis, machine learning, and explainability provides a concise and interpretable framework for predicting neck movement direction and can support applications in sports safety, automotive safety, clinical assessment, rehabilitation, and injury prevention.

System Design

The proposed system follows a modular pipeline that integrates biomechanical simulation, machine learning, and Explainable Artificial Intelligence. Initially, motion data are processed using OpenSim to generate relevant biomechanical features. The extracted data are then cleaned and prepared for machine learning. Different models are trained and evaluated to identify the most effective model for predicting neck movement direction during head impacts. LIME is integrated with the selected model to explain the factors influencing each prediction. The complete system can be connected to a web interface, backend API, and database, enabling users to upload data and obtain both predictions and explanations. This design provides an accurate, interpretable, and practical framework for neck-motion analysis in healthcare, sports, and safety applications.

System Architecture

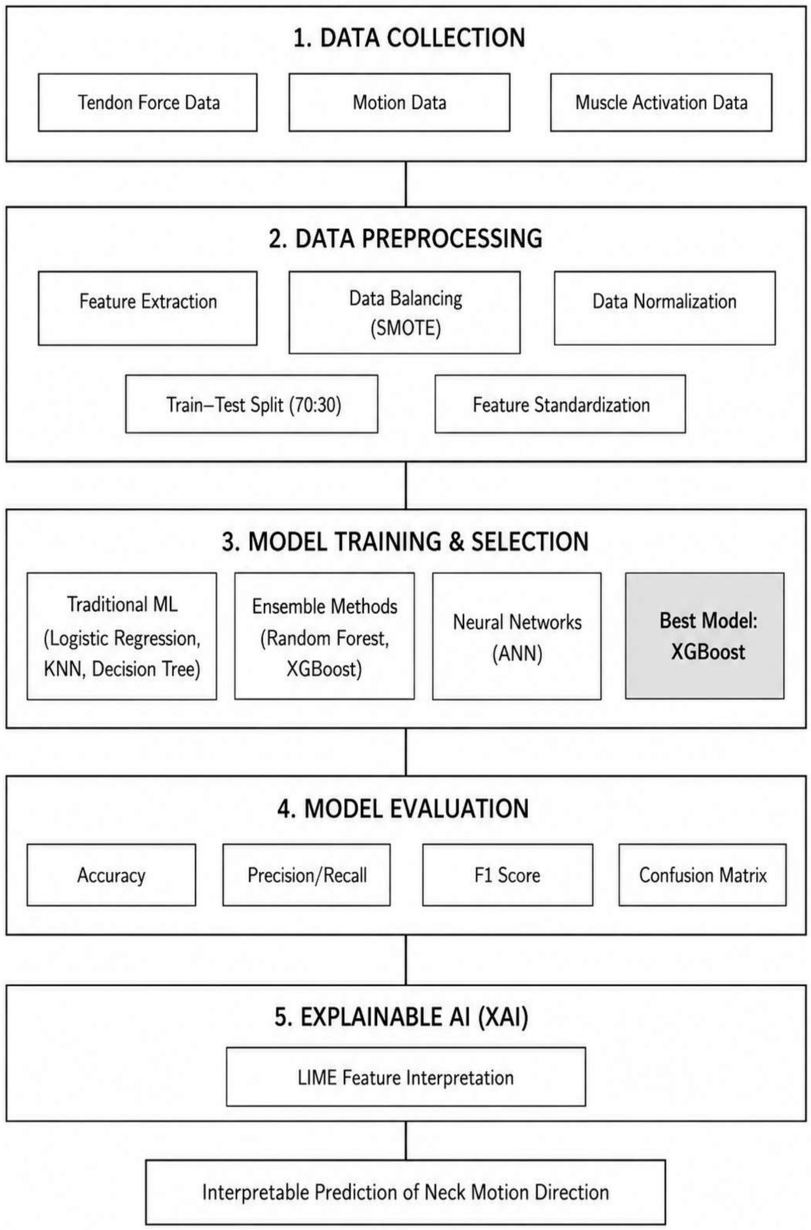

Figure 1 : System Design

System Architecture

The system architecture consists of seven sequential stages: Dataset Collection, OpenSim Simulation, Validated Tendon Force Data, Data Processing, ML/DL Model Development, XAI Integration, and Classification and Prediction. Each stage contributes to transforming raw motion data into an interpretable neck-direction prediction.

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1. Dataset Collection
The process begins with the collection of .mot motion files representing six different neck movement directions from multiple subjects. These data provide the basic information required for biomechanical simulation, model training, and performance evaluation.

2. OpenSim Simulation
The collected motion data are processed using **OpenSim** to simulate neck biomechanics. The simulation generates biomechanical parameters and tendon-force information for different movement conditions. The resulting data are stored in .sto files and used for further analysis.

3. Validated Tendon Force Data
The tendon-force data generated from OpenSim provide information about the forces acting on different neck muscles during head-impact conditions. These validated biomechanical features form the primary input for the subsequent data-processing and prediction stages.

4. Data Processing
The generated data are cleaned and prepared for machine learning. Noise and inconsistent values are addressed, while relevant features such as angular velocity, acceleration, and impact-force characteristics are extracted. **SMOTE (Synthetic Minority Oversampling Technique)** is applied to reduce class imbalance and improve model training.

5. ML/DL Model Development
The processed biomechanical features are supplied to machine learning and deep learning algorithms for neck-direction classification. Models such as **XGBoost and Neural Networks** are considered to identify the most suitable predictive approach. The models are evaluated using appropriate performance measures, and the best-performing model is selected.

6. XAI Integration
The selected machine learning model is integrated with Explainable Artificial Intelligence (XAI) using LIME (Local Interpretable Model-Agnostic Explanations). LIME identifies the input features that have the greatest influence on individual predictions. This provides users with an understandable explanation of why a particular neck movement class was predicted.

7. Classification and Prediction
In the final stage, the trained model predicts the neck movement direction from the processed biomechanical data. Along with the predicted class, the system provides the corresponding LIME-based feature explanation. The results can be displayed through dashboards or a web interface, allowing healthcare professionals, sports scientists, and safety researchers to interpret the prediction and use the information for further neck-injury analysis.

Development Tools
The development of the proposed system requires tools capable of handling biomechanical simulation, data processing, machine learning, Explainable AI, visualization, storage, and deployment. OpenSim provides the biomechanical simulation environment, while Python and its associated libraries support data analysis, machine learning, and explainability. XGBoost is used for high-performance classification, and LIME provides interpretation of model decisions. Together, these tools support the development of an accurate, reliable, and interpretable neck-motion prediction system.

Biomechanical Simulation Tool
OpenSim 4.4 is used for musculoskeletal modeling and simulation of head-impact dynamics. It accepts .mot motion data and calculates internal biomechanical quantities. The resulting .sto files contain information such as muscle forces, joint contact forces, and kinematic variables. OpenSim is used because it provides a structured environment for biomechanical analysis without requiring invasive measurement of internal forces.

Programming Language and Environment
Python 3.10+ is used as the main programming environment. Development can be performed using Jupyter Notebook, Visual Studio Code, or PyCharm. Python provides extensive support for machine learning, data processing, visualization, and Explainable AI, making it suitable for integrating the different components of the proposed system.

Data Processing and Analysis
The project uses Python-based data-processing libraries to clean, organize, transform, and analyze the biomechanical dataset. Machine learning and deep learning frameworks support model development, while LIME is used for prediction interpretation. Database systems such as MySQL or PostgreSQL can store user information, input data, predictions, and explanations. Motion files, tendon-force files, and trained model files can be maintained using local or cloud-based storage.

Visualization and Supporting Tools
Visualization tools such as Matplotlib and Plotly are used to present model results and feature contributions. Power BI can be used to prepare analytical reports and dashboards. These tools help convert prediction results and biomechanical information into graphical representations that are easier to understand.

4. Implementation Process

The implementation of the proposed Neck Motion Direction Prediction with Explainable AI system follows the workflow presented in the methodology framework. The implementation begins with the collection of biomechanical and sensor-based information and proceeds through preprocessing, machine-learning model development, performance evaluation, and explainability analysis.

4.1 Data Collection and Preparation

The implementation starts by collecting tendon force, motion, and muscle activation data representing different neck movement directions. Motion information is obtained from biomechanical measurements and OpenSim-based analysis, while tendon-force and muscle-activation variables provide additional information about the mechanical response of the neck during movement. Each data instance is assigned an appropriate movement-direction label for supervised learning.

The collected dataset is converted into a structured format in which each row represents an observation and each column represents a biomechanical or sensor feature. Missing, inconsistent, or invalid observations are identified and handled before further processing. The resulting dataset is then prepared for feature extraction and machine-learning analysis.

4.2 Data Preprocessing

The relevant predictive characteristics are extracted from the raw measurements. Features representing motion, force, and muscle activation are selected based on their relevance to neck movement classification. Since some movement categories may contain fewer observations than others, **SMOTE** is applied to the training data to generate additional synthetic samples for minority classes.

After balancing, the features are normalized and standardized so that variables with different numerical ranges can be processed consistently. The prepared dataset is subsequently divided into 70% training and 30% testing data**.** The testing portion is kept separate throughout the training process to provide an unbiased evaluation of the final models.

4.3 Model Development and Training

The training dataset is used to develop several classification models. Logistic Regression, KNN, and Decision Tree are implemented as traditional machine-learning models. Random Forest and XGBoost are implemented as ensemble learning approaches, while an Artificial Neural Network (ANN) is developed as a neural-network-based classifier.

Each model receives the same processed input features and is trained to predict the corresponding neck movement direction. Model parameters are adjusted using the training data, and the resulting classifiers are compared using the same evaluation criteria. The implementation framework identifies XGBoost as the best-performing model**,** which is subsequently used for the explainability stage.

4.4 Model Evaluation

After training, the models are tested using the reserved 30% test dataset. Performance is measured using accuracy, precision, recall, F1-score, and confusion matrix**.** Accuracy provides the overall percentage of correctly classified movement observations, while precision and recall indicate the model's ability to correctly identify individual movement classes. The F1-score provides a balanced measure of precision and recall.

The confusion matrix is generated to examine the classification behavior of each movement category and identify possible misclassification between similar neck movements. The model comparison enables the best-performing classifier to be selected based on its overall predictive performance.

4.5 XAI-Based Implementation

The final implementation stage integrates Explainable Artificial Intelligence (XAI) with the selected XGBoost classifier. **LIME** is applied to individual test observations to determine which input features have the greatest influence on the model's prediction. For each prediction, LIME produces a local explanation showing the features that contribute positively or negatively to the predicted movement direction.

The explanation can be used to determine whether motion characteristics, tendon force, or muscle activation variables are responsible for a particular prediction. This makes the prediction process more transparent and allows researchers and safety professionals to examine the reasoning behind individual classifications.

4.6 Complete Implementation Workflow

The complete implementation follows the sequence: Tendon Force Data + Motion Data + Muscle Activation Data → Feature Extraction → SMOTE Data Balancing → Data Normalization → Feature Standardization → 70:30 Train-Test Split → ML Model Training → Model Comparison → XGBoost Selection → Accuracy/Precision/Recall/F1/Confusion Matrix → LIME Feature Interpretation.

The implemented system therefore combines biomechanical information with machine-learning prediction and explainability. The resulting framework can identify neck movement direction while simultaneously providing information about the features responsible for each prediction, making it suitable for potential applications in sports injury prevention, automotive safety, clinical assessment, rehabilitation, and biomechanical research.

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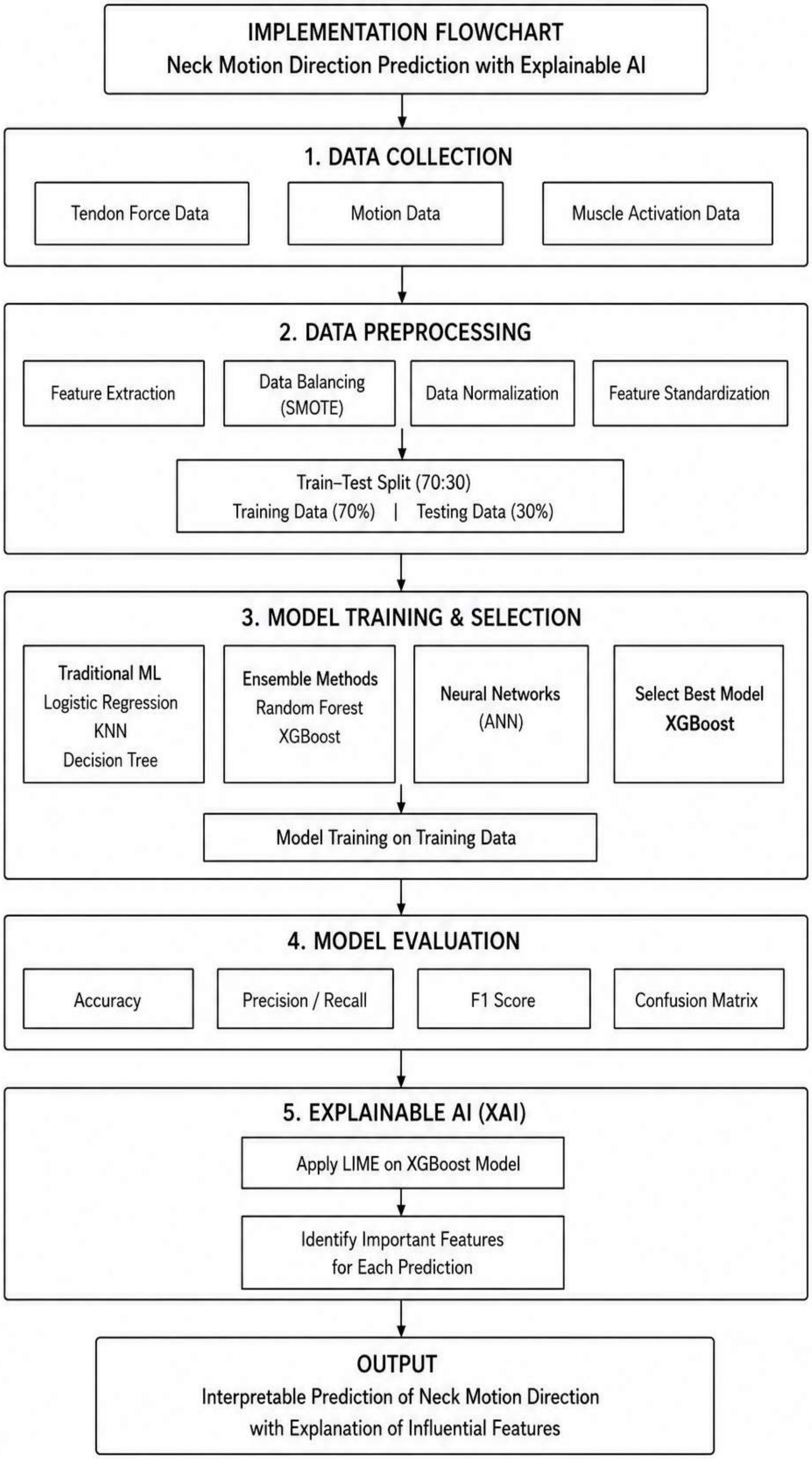

Figure 2: Implementation Flowchart

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Results

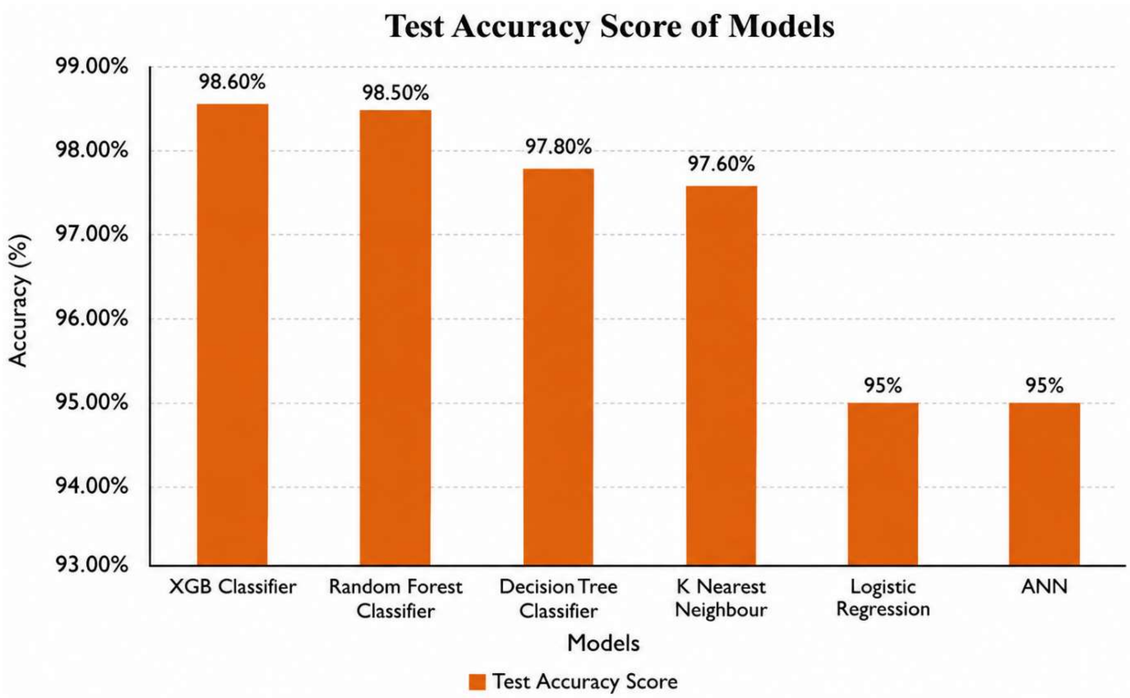

Figure 3 : Test Accuracy Score of Models

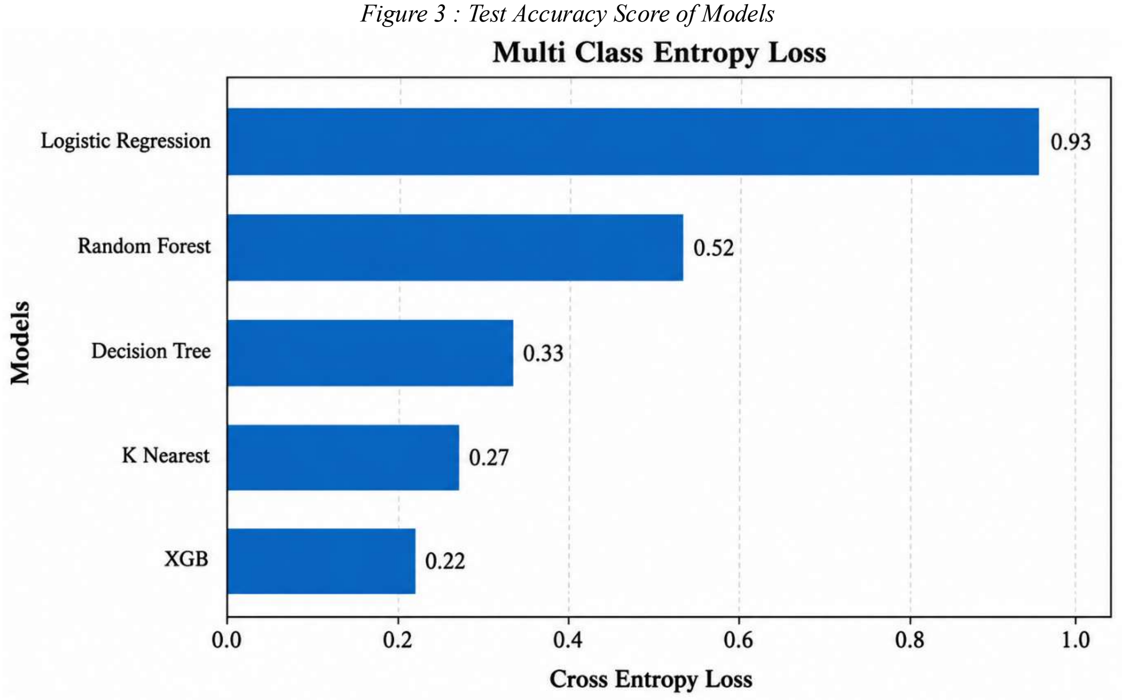

Figure 4 : Multi Class Entropy Loss

Figure 3 shows that the XGB classifier achieved the highest test accuracy of 98.60%, followed by Random Forest (98.50%), Decision Tree (97.80%), KNN (97.60%), Logistic Regression (95%), and ANN (95%). The results indicate that XGB provides

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the most effective prediction of neck motion direction.

Figure 4 shows that XGB obtained the lowest multi-class cross-entropy loss of 0.22, followed by KNN (0.27), Decision Tree (0.33), Random Forest (0.52), and Logistic Regression (0.93). Lower loss indicates better prediction confidence and probabilistic performance.

Overall, XGB demonstrates the best combination of high accuracy and low loss, making it the most suitable model for predicting neck motion direction in the proposed system.

Explainable AI Results
Instance 1: Flexion Football

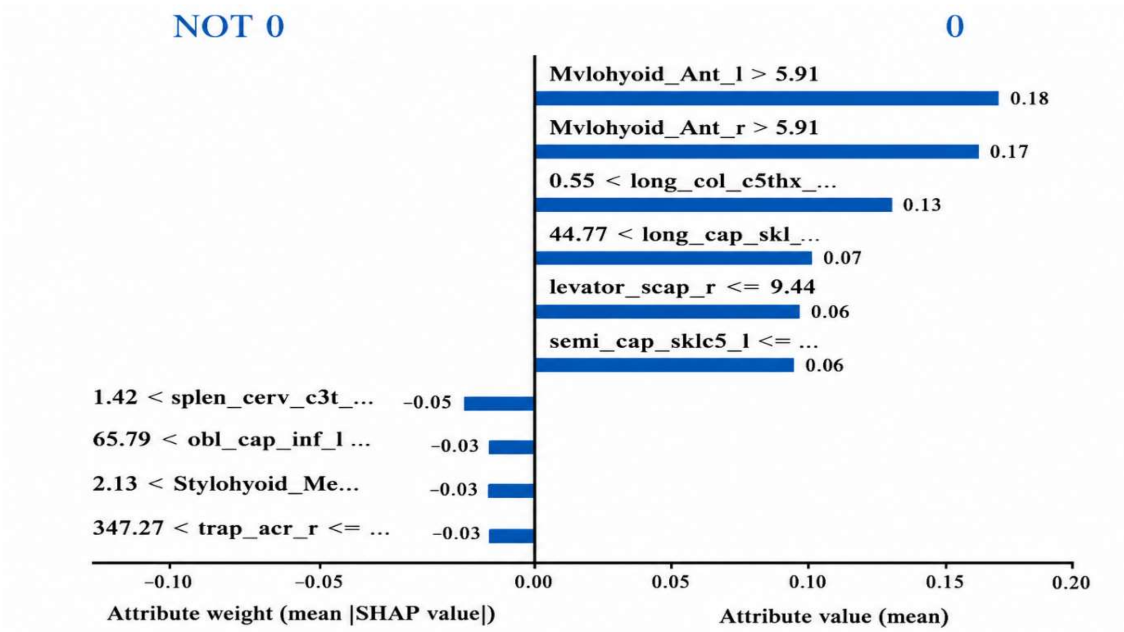
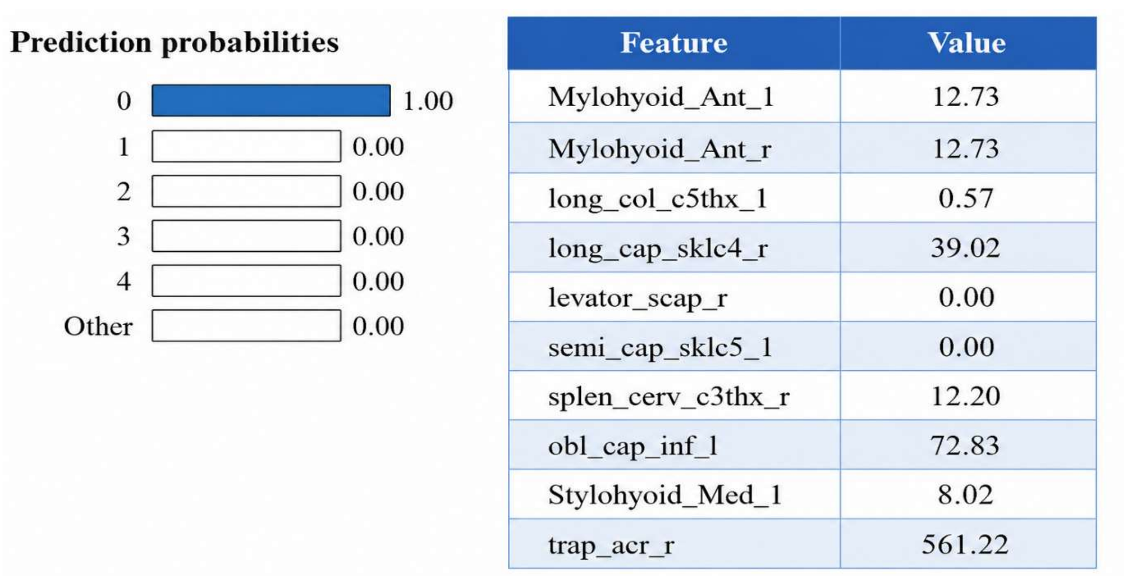


Figure 5: Top 10 confidence intervals of features with assigned weights and attributes



Feature	Value
Mylohyoid_Ant_1	12.73
Mylohyoid_Ant_r	12.73
long_col_c5thx_1	0.57
long_cap_sklc4_r	39.02
levator_scap_r	0.00
semi_cap_sklc5_1	0.00
splen_cerv_c3thx_r	12.20
obl_cap_inf_1	72.83
Stylohyoid_Med_1	8.02
trap_acr_r	561.22

Figure 6: Prediction Probabilities and Feature Values with Assigned Weights

Figure 5 presents the SHAP-based feature importance for the prediction of neck motion direction. The model predicts Class 0 with a probability of 1.00, indicating highly confident classification. The most influential features are Mylohyoid_Ant_l (0.18), Mylohyoid_Ant_r (0.17), and long_col_c5thx_1 (0.13), which have the strongest positive contributions toward Class 0.

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Other features, such as long_cap_sklc4_r, levator_scap_r, and semi_cap_sklc5_l, also contribute positively. In contrast, features such as splen_cerv_c3thx_r,obl_cap_inf_l, Stylohyoid_Med_l, and trap_acr_r have negative SHAP values, indicating that they reduce the likelihood of the Class 0 prediction.

Figure 6 further supports this prediction by showing that the model assigns a 1.00 probability to Class 0, while all other classes receive approximately zero probability. The corresponding feature values provide the physiological input values used by the model, with trap_acr_r (561.22) and obl_cap_inf_l (72.83) showing relatively large measured values. Overall, these results demonstrate that the XGB model provides a highly confident and interpretable prediction, while SHAP analysis identifies the specific muscle-related features contributing to the predicted neck motion direction.

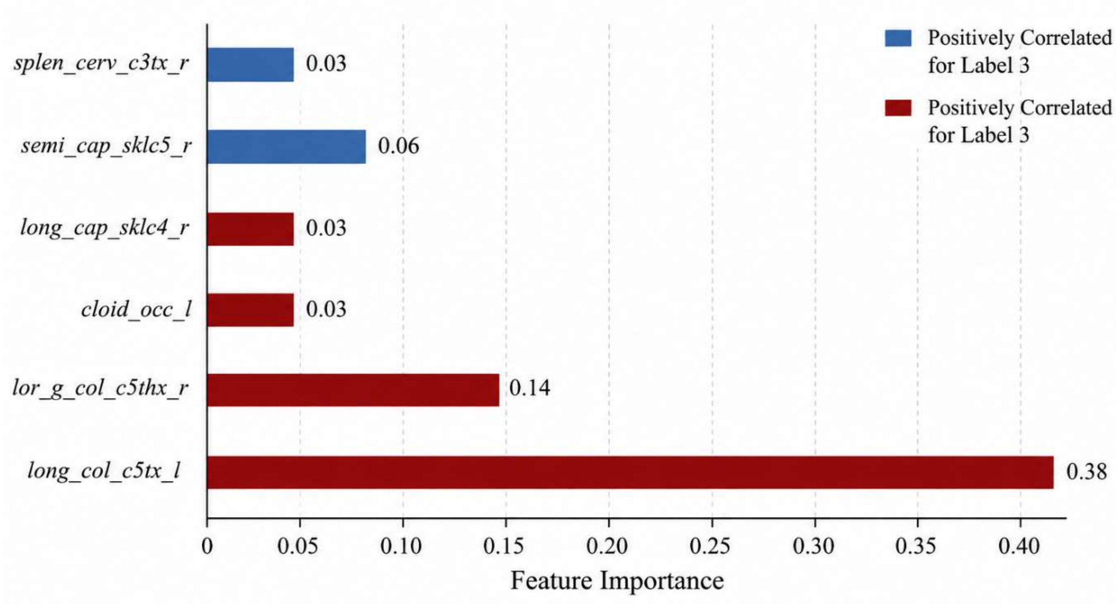

Figure 6 : LIME-Based Top Six Feature Importance for Local Interpretability of Class 3 Predictions

TABLE 1: LIME – Major Sub-Muscle Contribution to Prediction

Sub-muscles Major Contribution to Predict the Label	Actual Label	Predicted Label
Mylohyoid_Ant_r, Mylohyoid_Ant_l, long_col_c5thx, long_cap_sklc4_r	0 [Flexion football]	0 [Flexion football]
long_col_c5thx_l, long_col_c5thx_r, cleid_occ_l, long_cap_sklc4_l	3 [Lateral football]	3 [Lateral football]

Figure 6 presents the LIME-based local feature importance for Class 3 (Lateral football) predictions. The results show that long_col_c5tx_l is the most influential feature, with an importance value of 0.38, followed by lor_g_col_c5thx_r (0.14). Other contributing features include semi_cap_sklc5_r (0.06), splen_cerv_c3tx_r (0.03), long_cap_sklc4_r (0.03), and cleid_occ_l (0.03). The larger contribution of the longus colli and related cervical muscle features indicates their strong influence on distinguishing the lateral neck-motion class.

Table 1 further demonstrates the local interpretability of the model. For the Flexion football class (Label 0), the prediction is correctly classified as Label 0, with Mylohyoid_Ant_r, Mylohyoid_Ant_l, long_col_c5thx, and long_cap_sklc4_r identified as major contributing sub-muscles. Similarly, for the Lateral football class (Label 3), the actual and predicted labels are both 3, with long_col_c5thx_l, long_col_c5thx_r, cleid_occ_l, and long_cap_sklc4_l making major contributions.

Overall, the LIME results confirm that the model's predictions are locally interpretable and correctly classified, while identifying the specific sub-muscle features responsible for each prediction. The consistent contribution of cervical muscles, particularly the longus colli, highlights their importance in distinguishing different neck-motion directions.

Software Testing

Software testing is performed to verify the accuracy, reliability, interpretability, and overall functionality of the proposed system. Since the system combines OpenSim-based biomechanical processing, machine learning, Explainable AI, and a web interface, testing is conducted at different levels to ensure that individual components and the complete workflow operate correctly.

Unit Testing

Unit testing evaluates individual system components independently. The OpenSim module is tested to verify correct processing of **.mot files**, generation of **.sto files**, and extraction of biomechanical features. The preprocessing module is checked for data cleaning, scaling, SMOTE implementation, missing values, and potential data leakage. The machine learning module is tested to ensure that the trained XGBoost model can be loaded correctly and generate predictions for valid inputs. The XAI module is evaluated to confirm that LIME generates appropriate explanations and feature-importance visualizations. API endpoints are also tested with both valid and invalid inputs. **Pytest** and **unittest** can be used for these tests.

Integration Testing

Integration testing verifies the interaction between the different modules of the proposed system. The complete processing sequence is tested from motion-file upload through OpenSim simulation, feature extraction, machine learning prediction, LIME explanation, and final web-interface presentation. Data formats are checked at each stage to ensure compatibility between OpenSim outputs and machine learning inputs. Database operations are also tested to confirm that prediction results and explanations are stored correctly.

System Testing

System testing evaluates the complete application under realistic operating conditions. Functional testing verifies whether different motion files are processed correctly and whether the appropriate neck movement category is predicted. Accuracy testing compares model predictions with the corresponding ground-truth labels, with a target accuracy above 95%. Usability testing evaluates whether doctors, coaches, and researchers can easily upload data, view predictions, and understand the generated explanations. Performance testing examines response time, memory utilization, and system behavior when multiple files are processed.

Validation and XAI Testing

Because the proposed system is intended for biomechanical and healthcare-related analysis, additional validation is required. Explainability testing verifies whether LIME-generated feature contributions are consistent with expected biomechanical relationships. Robustness testing evaluates system behavior when noisy, incomplete, or inconsistent motion data are supplied. Security testing examines file-upload validation and database access controls to reduce the possibility of unauthorized or harmful input.

Test Data and Evaluation Metrics

Testing uses a reserved portion of the dataset together with additional simulated **.mot files**. The machine learning models are evaluated using **accuracy, precision, recall, and F1-score**, while the application is assessed using response time and throughput. User-interface evaluation can additionally consider user satisfaction and ease of use. These tests collectively determine whether the proposed system provides reliable predictions, understandable explanations, and stable overall performance.

Conclusion

The proposed research developed an Explainable AI-based framework for predicting neck movement directions during simulated head impacts using biomechanical tendon-force data. OpenSim was employed to obtain relevant kinematic and kinetic information, which was subsequently processed using machine learning techniques. Among the evaluated algorithms, XGBoost demonstrated strong classification performance for the six defined neck movement conditions.

An important contribution of the work is the integration of LIME with the XGBoost classifier. Instead of providing only a predicted movement class, the system identifies the biomechanical features that contribute to individual predictions. This provides clinicians and researchers with additional information for understanding the relationship between muscle forces and neck movement during different loading conditions.

The proposed framework can support the analysis of neck responses under different impact conditions and may be useful in sports science, rehabilitation, biomechanics, and safety-related applications. The combination of predictive accuracy and interpretability improves the practical value of the system by helping users understand the reasons behind model outputs. The reported experimental results demonstrate the potential of the proposed approach as an interpretable decision-support system for neck-motion analysis.

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