The Impact of Human Posture on Prevention of Neck Musculoskeletal Disorders: A Multivariate Time-Series Prediction Approach Using LSTM

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Abstract

Introduction: Bending is an essential human movement that requires precise coordination between muscles and organs for optimal performance. "Text Neck Syndrome" refers to pain resulting from poor neck posture when looking down at a phone for long periods. Many studies link forward head posture or neck curvature to various tasks, particularly while using mobile phones and computers. The weight exerted on the neck increases significantly as the degree of curvature increases. However, this increase has not been adequately correlated with the duration of neck curvature, which is a critical factor influencing changes in neck weight over time and its negative health impacts, especially on the cervical vertebrae. **Aim:** In this paper, two distinct solutions are proposed. **Methods:** The first is a mathematically derived model that considers factors such as head weight and bending duration as critical determinants affecting the efficiency of neck movement. This model analyzes the relationship between skull weight, bending angle, and time to achieve maximum motor efficiency. The second solution employs a multivariate time-series prediction approach using an LSTM model based on the multiple_IMU dataset. This method determines the extent of the problem and provides alerts for the allowable duration of neck bending. The model incorporates factors such as skull size, weight-to-height ratio, and other parameters to evaluate the impact. **Results:** the results demonstrate high accuracy and robust performance, with the LSTM model achieving a test loss of 0.00046, a test mean absolute error (MAE) of 0.00925, an accuracy of 98.93%, and an F1 score of 0.9935, which is higher than that of other Deep Learning models such as CNN and GRU. **Conclusions:** These findings underscore the potential of mathematical modeling and AI-based techniques in addressing the health challenges posed by prolonged poor neck posture.

Keywords: Text Neck Syndrome, Inertial Measurement Unit, Head Posture, Human Neck, Neck Curvature, Deep Learning, Long Short-Term Memory, Forward Head Posture.

Introduction

Recent scientific research has increasingly utilized artificial intelligence (AI) algorithms across various fields, including static solutions[1] and AI-driven approaches,[2] to address complex problems reliably. AI has gradually become part of most current research trends, also integrating AI with other technologies such as utilizing YOLOv5s for detecting rice diseases and a CNN for classifying them into nine categories. The detection model identifies affected areas, which are then extracted for classification. The CNN achieved 97.28% accuracy, while YOLOv5s

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reached 94.60%;[3] the hybrid model can be applied to solve problems as in Fatlawi *et al.*[4]. Data mining is essential in the digital age, especially with the increasing size and variety of data. Traditional methods for classifying and clustering large datasets are often resource-intensive due to the growing number of data attributes. To address this, attribute reduction plays a crucial role in optimizing data pre-processing by minimizing computational requirements. This study presents a hybrid model that eliminates irrelevant attributes using K-Means Clustering and a Bagging Ensemble Classifier, evaluated with multiple metrics. Tested on five datasets, the model reduces attribute count by up to 70%, enhancing classification efficiency by decreasing computation time.

A study in Naji and Alwan[5] presents a multi-step approach framework for human activity prediction consisting of three stages: Wavelet Transform (WT) to reduce noise, feature extraction and classification with a hybrid LSTM-CONV1D model based on four benchmark datasets—UCI-HAR, M-health, WISDM, and PAMAP2 with high accuracy. Additional evaluation on UCI-HAR achieved 98.92%, confirming the model's reliability in forecasting sequential activities, while Authors in Formica *et al.*[6] introduce a novel arrhythmia detection model Wavelet Transformation (WT) and Power Spectral Density (PSD) are utilized for feature extraction in the frequency domain, termed OWSK, which integrates One-Sided Selection (OSS) demonstrates significant improvement, Support Vector Machine (SVM), and K-Nearest Neighbour (KNN) algorithms to classify four types of ECG heartbeats using an inter-patient scheme.

Understanding the effect of specific factors such as head weight and bending time is required for many daily activities, such as kneeling, picking up objects, and performing physical exercises. Proper bending skills can be achieved through strengthening exercises that target the muscles responsible for bending and by improving balance and motor coordination.

Normal solution methods such as (focus on anti-tuberculosis medications) for such cases condition[7] resulting from Mycobacterium tuberculosis primarily damage the vertebrae, often leading to spinal deformities, which sheds light on Pott disease, a spinal infection caused by tuberculosis.

Using common symptoms, such as persistent back pain, stiffness, and potential nerve-related problems, stressing the importance of early detection. Advanced imaging techniques like MRI and CT scans for diagnosing the disease accurately.

However, prolonged bending places significant pressure on the cervical spine and surrounding muscles, potentially leading to symptoms such as headaches, dizziness, muscle stiffness, and chronic issues such as spinal disorders or permanent curvature. "Text neck" syndrome, a condition resulting from poor posture while using devices, can cause pain or inflammation of the joint facets in the neck and shoulder region.

This study aims to analyze the effect of posture influenced by various factors, such as smartphone usage, on head and neck angles among college students. The weight of an adult head in a normal vertical posture, with ears aligned to the shoulders, is approximately 4.5-5.4 kg. When the head is tilted forward, the force exerted on the neck increases significantly: at 15°, 30°, 45°, and 60° angles, the force rises to 12.3, 18.2, 22.3, and 27.3 kg, respectively.[8]

Smartphone posture significantly influences the musculoskeletal load on the neck.[9] Muscle activation levels during phone usage while walking were 21.2% and 41.7% higher than when sitting and standing, respectively ($p < 0.01$). Furthermore, head vertical and angular accelerations were significantly greater during walking than sitting and standing ($p < 0.01$). Participants exhibited more head flexion and increased neck extensor muscle activation ($p < 0.01$) when texting compared to browsing ($p < 0.01$).

A study by Namwongsa *et al.*[10] investigating the prevalence of musculoskeletal disorders (MSDs), particularly neck pain, among smartphone users in Thailand surveyed 779 undergraduate students. 32.5% of respondents reported neck pain, with associated factors including prolonged neck flexion and smoking. The findings highlight the need for interventions to mitigate neck pain among smartphone users.

Figure 1 illustrates different neck postures, where the blue line represents the neck, the red line represents the head, and angles indicate the degree of tilt. This paper introduces two main contributions: (1) a mathematical model demonstrating the relationship between bending time and neck weight and (2) a Multivariate Time-Series Prediction model using LSTM-based IMU datasets.[11]

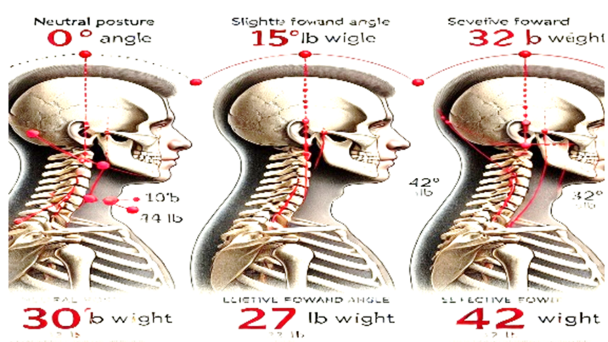


Figure 1: Head and Neck Posture.

Posture is categorized into three types: Normal Posture: The head and neck are aligned without forward tilt. Slight Forward Head Posture: The head and neck display a slight forward tilt. Severe Forward Head Posture: The head and neck exhibit a pronounced forward tilt.

The Effect of Head Weight on the Bending Process

The weight of the head is a critical factor affecting the bending process. Excessive head weight increases the effort required to perform specific movements, as it demands additional force to overcome gravity. This added pressure on the spine and surrounding muscles elevates the risk of injuries and muscle fatigue. Ergonomic seat design criteria should be carefully considered to minimize the harmful effects of prolonged computer or smartphone use. A study by Betsch *et al.*[12] involving 50 participants (average age 25.3 years; 52% male; mean BMI 22.8) measured standing posture. Dynamic measures involving 34 participants (average age 25.4 years; 53% male; mean BMI 22.7) highlighted demographic characteristics. Dugailly *et al.*[13] examined head-neck stiffness using controlled forces to rotate participants' heads relative to their torsos. These "passive" stiffness measurements minimized muscle activity, emphasizing the influence of head weight on posture.

A cephalometric study by Xiao *et al.*[14] assessed head and cervical posture in 384 individuals with and without temporomandibular disorders (TMDs). Patients were grouped as TMD-free, TMD without TMJ pain, and TMD with TMJ pain. Results indicated that patients with TMJ pain exhibited more pronounced forward head posture (FHP), worsening with TMD severity. Similarly, Gao *et al.*[15] demonstrated that cervical curvature alterations affect neck muscle tension, impacting mandibular movement and function and potentially contributing to TMD development.

The Effect of Bending Time on the Bending Process

Bending time (the initiation of bending relative to total movement duration) plays a pivotal role in movement performance. Optimal bending timing enhances efficiency and balance, while incorrect timing may result in imbalance and reduced movement power.

The main Contributions of this paper are:

1. A comprehensive understanding of the effects of bending, head weight, and bending time on body performance.
1. Justifications and techniques for improving bending performance and reducing injury risks.
2. An LSTM model for efficient prediction of bending effects over specific durations, supporting its potential use as a diagnostic tool in sports training and medical treatment.
3. Various deep learning models, including Convolutional Neural Networks (CNNs) and Gated Recurrent Units (GRUs), have been explored for time-series prediction. However, Long Short-Term Memory (LSTM) networks were selected due to their strong capability to capture long-term dependencies within sequential data. Unlike CNNs, which are more effective for spatial data processing, LSTMs are well-suited for analyzing temporal patterns, making them an appropriate choice for predicting neck posture over time. Although GRUs offer computational efficiency, they may struggle with handling extremely long sequences, which is a crucial aspect of this study.

Literature Survey

This paper introduces a Proposed Neck Load Prediction model to predict the force required to support increased head weight during prolonged bending. The model aims to quantify how neck load changes with extended smartphone misuse. Employing (AI) techniques in research enhances quality, efficiency, and effectiveness. Below, we discuss various studies and methods relevant to understanding the impact of bending, head weight, and bending time on the human body.

AI and Wearable Technology for Posture Analysis

- A novel method combining wearable technology and Convolutional Neural Networks (CNNs) introduces a sensor-equipped device for real-time posture tracking.[16] This approach aids in precise posture assessment for various applications.
- Improved experimental operation techniques by Montgomery *et al.*[17] enhance research quality by optimizing experimental decisions, identifying key variables, and refining data analysis.

Effects of Smartphone Usage on Neck Posture

- A cross-sectional study involving 80 college students revealed that 51.3% experienced moderate to severe neck pain due to smartphone use.[18]
- A cohort of 145 adolescents was analyzed to develop a diagnostic framework for Forward Head Posture (FHP). Data from 70% of participants were used for model training, with sagittal alignment parameters incorporated, and the remaining 30% validated the framework.[19] The study highlights age-related spinal alignment evolution and differences in smartphone usage patterns.[20]
- A study of 384 participants found a correlation between temporomandibular joint pain and increased forward head posture. This condition worsened with the severity of temporomandibular disorders.[14]

Cervical Spine Analysis and Head Posture Monitoring

- The craniometrical junction (C0–C1 joint) exhibited significant flexion angles during smartphone use, with mean angles of 33.33°, 27.50°, and 32.03°. Subaxial (C2–C7) segments showed lower angles, highlighting the C0–C1 joint's primary role in neck flexion.[21]
- A system employing three IMU sensors accurately monitored head posture, showing promise for applications in physical therapy and rehabilitation.[22]
- Machine learning models have demonstrated high accuracy (90–98%) in classifying head positions using IMU sensors. Multimodal approaches combining various sensor data types achieved superior results compared to unimodal systems.[23-25]

Advancements in Wearable Technology

- Reviews by Huang *et al.*[26] and Camboim *et al.*[27] emphasize advancements in wearable systems for posture monitoring, discussing sensor types, placement, and applications in healthcare and virtual/augmented reality. Future research should focus on enhancing data accuracy, user comfort, and device durability.
- Real-time posture correction systems utilizing IMU sensors were proposed by Tilili *et al.*[28], offering feedback to prevent musculoskeletal issues.
- Inductive textile sensors integrated into wearable devices provide continuous back movement monitoring for ergonomic improvements.[29]

- Wireless systems employing IMU sensors enable unobtrusive, real-time posture monitoring, aiding rehabilitation and ergonomic assessments.[29]

Method

This section introduces three aspects: the dataset description used to train the DL model, the show mathematical problem with proof, and the proposed DL solution in detail.

Dataset Analysis and Description

The dataset used in this study focuses on deep learning applications to predict the force exerted on the neck over time due to bending.

Input Shape: X:(45076,20,3)X:– 45,076 samples with 20 time steps and 3 features per step.

Output Shape: y:(45076,)y: – Target values corresponding to each input sample.

Data Pre-processing involves two main aspects:

Class Imbalance: The dataset exhibits a heavy concentration of values between 0.7 and 0.8, risking model bias. Techniques such as class balancing or reweighting are necessary.

Irregular Patterns: Figure 2 illustrates occasional spikes and fluctuations in values (e.g., Roll_S1), with sudden drops and rises potentially indicating outliers or sensor errors.

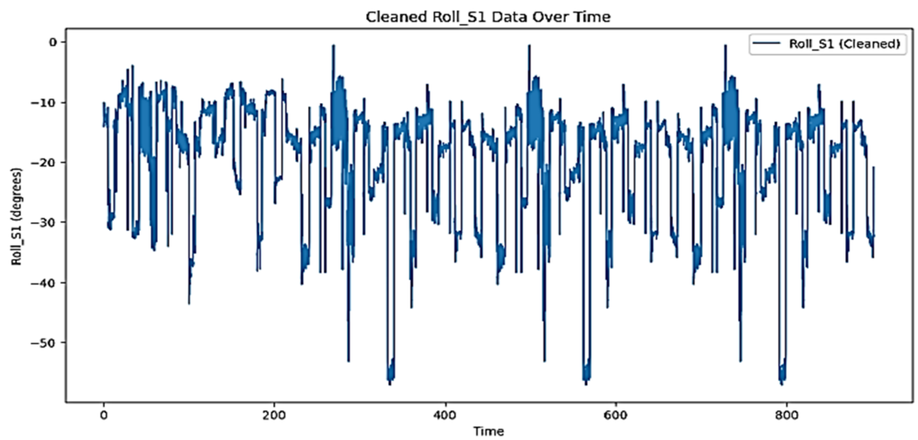


Figure 2: A time-series Plot of the Variable Roll_S1 Against TimeRoll_S1_diff Analysis (Figure 3).

The Roll_S1_diff feature, shown in Figure 3, exhibits small-magnitude differences with rapid fluctuations, oscillating between negative and positive values. Notable observations include:

Spikes: Several positive and negative spikes indicate abrupt changes or significant events in the original data. The maximum value approaches 40, while the minimum is around -20.

General Trend: The data primarily fluctuates around 0, with changes between consecutive time points being small and balanced between increases and decreases.

Noise Characteristics: The Roll_S1_diff feature appears noisy, and characterized by random, high-frequency oscillations. These fluctuations become more pronounced after Time ~300, suggesting increased variability or external influences during this period.

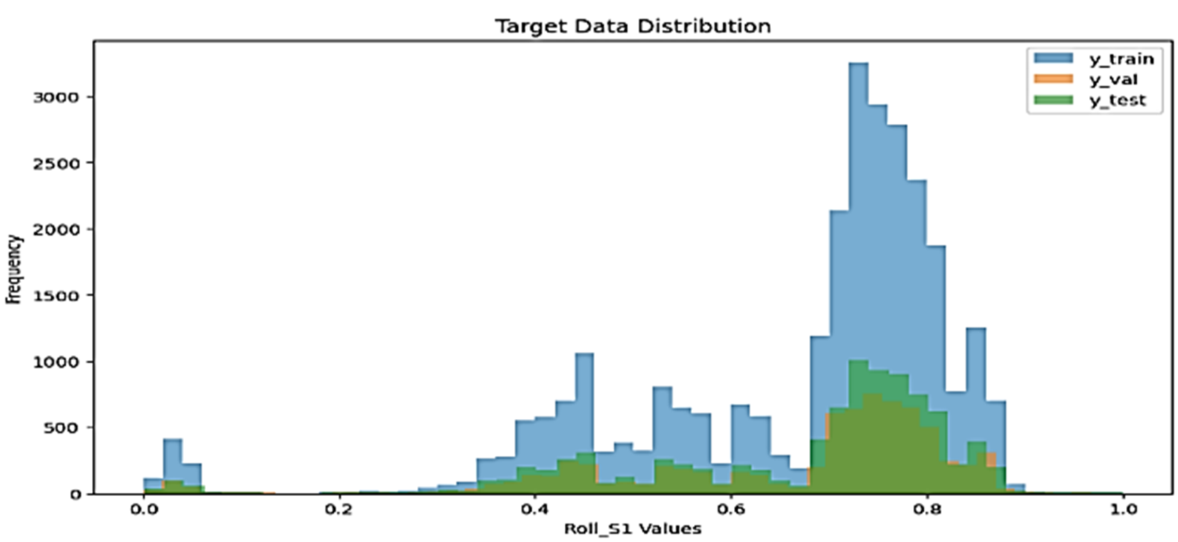


Figure 3: Difference Feature of Roll_S1 Data, Named Roll_S1_diff.

Figure 4 presents the histogram of the Roll_S1 data, depicting the distribution across training, validation, and test sets. Key observations include:

Prominent Peaks: A significant peak in the training set occurs between 0.7 and 0.8, with the highest frequency exceeding 3000.

A secondary, smaller peak is observed between 0.5 and 0.6. Minor spikes below 0.4 occur less frequently, especially in the validation and test sets.

Skewness: The distribution is right-skewed, with the majority of data points concentrated between 0.4 and 0.9. Values below 0.4 are relatively rare, and extremely low values near 0 are almost non-existent.

Set Differences: Compared to the training set, the validation and test sets exhibit more even distributions across lower values (below 0.4). This variation could result in slightly different behavior during model validation and testing.

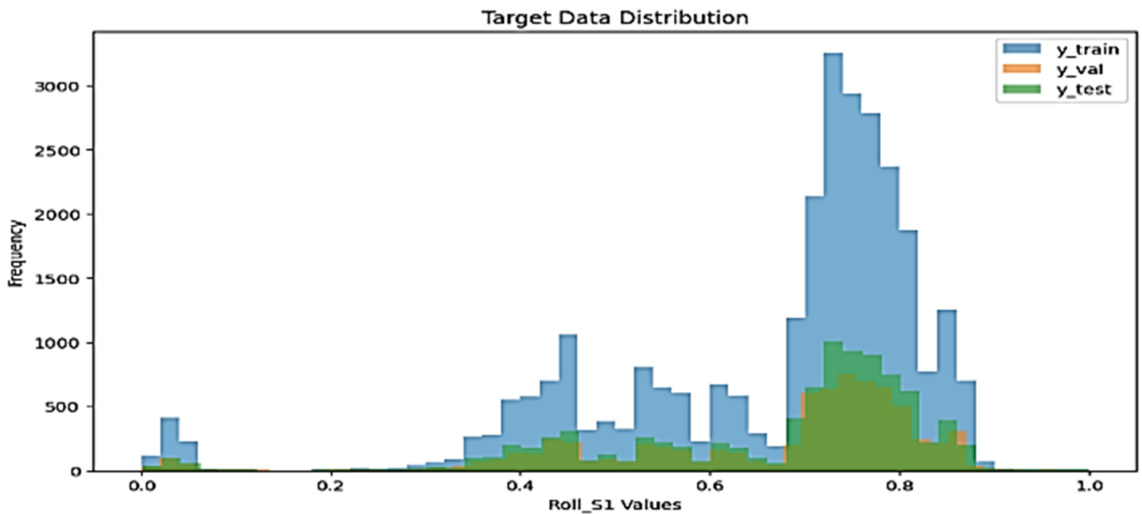


Figure 4: Target Data Distribution for the Variable Roll_S1.

Ethical and Practical Considerations

Implementing IMU-based posture monitoring presents several challenges that must be addressed:

Privacy Issues: Continuous tracking of posture data raises concerns about user privacy. Protecting this information through encryption and anonymization is crucial.

User Acceptance: The effectiveness of wearable sensors depends on user comfort and ease of adoption. Future studies should focus on developing lightweight, non-intrusive designs.

Real-World Application: Variability in user behavior and environmental conditions can affect model accuracy. Incorporating adaptive learning techniques can improve system reliability.

Description of Mathematical Problem

The following aspects represent the main key points in this work:

The Relationship between Increased Head Weight and Neck Curvature

When the head moves forward at an angle while using a mobile phone, the weight bore by the neck increases, amplifying the force bending the neck, as represented by Equation (1). Considering the head and neck as two connected points, the relationship between force and angle can be expressed through the physical law:

$$F=m\times a \quad (1)$$

where:

F is the applied force (additional head weight). m is the mass (increased head weight). A is the acceleration (the change in speed due to pressure).

When the head tilts forward at an angle, the neck experiences a downward compressive force. This force changes the speed of head movement, requiring the neck to support the added weight. Assuming the normal head weight is WWW, the effective weight acting on the neck when tilted at an angle θ increases to W′. The relationship is:

$$W'=W\times\cos(\theta) \quad (2)$$

Thus, as the angle θ increases, the effective weight W′ acting on the neck also increases.

A Mathematical Representation

To quantify the impact of bending, the increased head weight, and the time required for bending, we define the following variables:

- W: Normal weight of the head,
- θ: Angle of forward bending,
- t: Time taken for bending.

Using the concept of work (force × distance), the force acting on the neck due to the increased head weight can be described as:

$$F=W'-W \quad (3)$$

W′ is the weight acting on the neck as a result of bending, and it can be calculated using the relationship:

substituting $W' = W \times \cos(\theta)$ into equation (3)

$$F = W \times (\cos(\theta) - 1) \quad (4)$$

The work done by this force over a distance can be expressed as:

$$Work = F \times t \quad (5)$$

Combining these equations, the total work done to support the additional head weight over time t is:

$$Work = W \times (\cos(\theta) - 1) \times t \quad (6)$$

This equation quantifies the work required by the neck to counteract the effects of the head tilting at angle θ over a duration t.

Constraints on Variables

To make the model realistic, the following limits can be applied:

- **Head Weight (W)**: For adults, it typically ranges from 4.5 to 6 kg; for estimation, it can be set between 4 and 7 kg.
- **Bending Angle (θ)**: Can range from 0° (neutral position) to 60° (major curvature). For improper phone use, limits of 0° to 45° are reasonable.
- **Bending Time (t)**: Ranges from a few seconds to several minutes. A practical range is 5 seconds to 10 minutes.

Validation of the Mathematical Model Using Work-Energy Principles

The work W done by the force F is the product of force and the distance (d) over which the body moves:

$$W = F \times d \quad (7)$$

From Equation (4), the force F is expressed as $F = W \times (\cos(\theta) - 1)$. The distance d, representing the bending motion, can be calculated assuming a constant bending speed v:

$$d = v \times t \quad (8)$$

Substituting F and d into Equation (7):

$$W = [W \times (\cos(\theta) - 1)] \times (v \times t) \quad (9)$$

By cancelling W (if $W \neq 0$) on both sides:

$$1 = (\cos(\theta) - 1) \times (v \times t) \quad (10)$$

Rearranging this, the product v×t which represents the bending distance over time is given by:

$$v \times t = 1/(\cos(\theta) - 1) \quad (11)$$

The relationship describes the effect of head bending and increased weight on the neck over time

Proposed Method

DL models such as (CNNs) and (GRUs) have been widely used for time-series prediction. However, this study employs (LSTM) networks due to their higher ability to retain long-term dependencies in sequential data. While CNNs are more effective for processing spatial information, LSTMs are particularly well-suited for capturing temporal patterns, making them an optimal choice for tracking neck posture over time. Although GRUs are computationally efficient, they may face challenges when dealing with very long sequences, which is a key consideration in this research. The proposed approach utilizes an LSTM model with hyperparameter tuning to predict roll data from multivariate time-series data. The methodology encompasses data pre-processing, feature engineering, hyperparameter optimization, and performance evaluation.

Multivariate Time-Series Prediction Using LSTM

The proposed method can be described as:

Input

- Dataset D
- Sequence length L
- Hyperparameter search space H

Output

- Trained LSTM model with optimized hyperparameters
- Evaluation metrics

Steps

Data Preprocessing:

- **Load Dataset:** Import dataset D containing time-series features (e.g., Time, Roll_S1).
- **Feature Engineering:** Compute the first-order difference feature for Roll_S1:

$$\Delta Roll\_S1[t] = Roll\_S1[t] - Roll\_S1[t-1]$$

Replace missing values with 0.

- **Normalize Features:** Scale all features to [0,1] using Min-Max scaling.

Sequence Construction: Generate overlapping sequences of length L:

$X[i]=D[i:i+L]$, $y[i]=D[i+L, Roll\_S1]$ where X[i] represents the input sequence, and y[i] represents the target value.

Data Splitting: Split the dataset into training, validation, and test sets using an 80-20 ratio.

Model Definition and Tuning:

- Design an LSTM-based model with the following architecture:
  - **Layer 1:** LSTM with u_1 units ($u_1 \in H$) and dropout rate p_1 ($p_1 \in H$).
  - **Layer 2:** LSTM with u_2 units ($u_2 \in H$) and dropout rate p_2 ($p_2 \in H$).
  - **Output Layer:** Dense layer with a single neuron.
- Hyperparameter Optimization:
  - Use random search with a maximum of T trials to optimize hyperparameters:

$$H=\{u_1,u_2 \in [64,128], p_1,p_2 \in [0.2,0.4], lr \in \{10^{-3},10^{-4}\}\}$$

  - The objective is to minimize validation Mean Absolute Error (MAE).

Model Training: Train the optimized model on the training set using early stopping based on validation loss.

Model Evaluation: Evaluate the trained model on the test set and report metrics such as loss and MAE.

This method is described in Algorithm 1:

Algorithm1: Multivariate Time-Series Prediction Using LSTM

Input: Dataset (D)

Output: Predicted Output ($\hat{y}$):

Data Preparation**:**

- Load dataset D={Time,Roll_S1,…}
- Compute temporal feature: Roll_S1_diff=Roll_S1[i]−Roll_S1[i−1],fill missing values with 0.
- Normalize features using Min-Max scaling.

1. **Sequence Construction:**

- Generate sequences of length L: X[i]={Fscaled[i],…,Fscaled[i+L−1]},y[i]=Fscaled[i+L,oll_S1]
- Data Splitting: Split (X,y) into (Xtrain,ytrain) (Xval,yval), and (Xtest,ytest) using an 80-20 ratio.

2. **Model Definition:**

- Design LSTM model: with tunable parameters: h_1=LSTM(u_1,d_1),h_2=LSTM(u_2,d_2),y^=Dense(1)
- Comple using Adam optimizer (lr)and MSthe: $\sum_{i=1}^{N}(yi - y_i^{\wedge})^2$

3. **Hyperparameter Tuning:**

- Optimize using random search.
- u1,u2∈{64,128}, d1,d2∈[0.2,0.4], lr∈{10−3,10−4} using Random Search.
- Stop early if ΔLval <ϵ for p consecutive epochs.

1. **Evaluation:**

Testmoel on (Xtest,ytest) the and the e superscript base, divide open paren yi minus y sub i. to theMA=$\frac{1}{N}\sum_{i=1}^{N} \mid (yi - y_i^{\wedge})^2 \mid$.
End

Hyper-parameter Configuration

The hyper-parameters used in this study are summarized in Table 1. These settings enable the LSTM model to effectively capture temporal dependencies in the dataset.

Table 1: Hyper-parameter Configuration for LSTM Model.

Hyperparameter	Value	Description
Learning Rate (lr)	$\{10^{-3},10^{-4}\}$	LR governs the step size for weight updates in the Adam optimizer.
Batch Size	Default (TensorFlow)	Training samples per training batch.
Epochs	30	Maximum number of training epochs.
Early Stopping	Patience=5	Prevent excessive training, and ensure optimal performance.
Dropout Rate (p1,p2)	{0.2, 0.4} tannable	Prevent overfitting, and enhance model generalization.
Sequence Length (L)	20	Number of subsequent timesteps in each input sequence length.
Number of Trials	5	Maximum trials during hyperparameter tuning
Input Layer	(seq_length=20)	The sequence length (number of features) determines the input shape
LSTM Layer 1 units (u_1)	{64, 128}	Number of units is selected via hyperparameter tuning. Activation tanh recurrent_activation = sigmoid
LSTM Layer 2	{64, 128}	Number of units is selected via hyperparameter tuning.
Dense Layer	Units = 1	Linear activation for single output prediction.
Optimizer	Adam(lr)	Adaptive learning rate tuned to optimize performance.
Loss Function	MSE	Metric for training loss computation

Experimental Results

The model's generalization and robustness are evident from the low validation and test errors, demonstrating its ability to generalize effectively to unseen data. The combination of a high R^2, low Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) indicates that the model captures underlying data patterns with high predictive accuracy. Furthermore, the nearly perfect F1 score and minimal misclassifications highlight the model's strength in classification tasks.

Performance Metrics described in Table 2 summarize the model's performance across key evaluation metrics, confirming its suitability for the problem domain by balancing accuracy, generalization, and robustness.

Validation MAE (val_mae): During hyperparameter tuning, the lowest validation MAE achieved was 0.0081, indicating minimal differences between predicted and actual values during validation.

Elapsed Time: The tuning process required approximately 20 minutes, suggesting a reasonable computational cost relative to the task complexity.

Model Performance on the Test Set involves the following:

Loss and MAE: The test loss was 0.00046, and the test MAE was 0.00825, reflecting the model's strong generalization to unseen data.

RMSE: The RMSE was 0.0214, indicating a low average magnitude of prediction errors.

MAPE: The relatively high MAPE of 77.99% may result from small target values inflating percentage-based metrics. This metric requires contextual interpretation and may not provide meaningful insights for this dataset.

R^2: The R^2 score of 0.983 demonstrates that the model explains 98.3% of the variance in the data, showcasing excellent predictive power.

Accuracy and F1-Score: With a classification accuracy of 98.9% and an F1-score of 0.993, the model performs robustly across all classes.

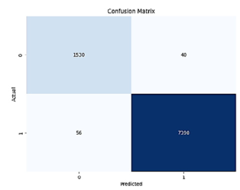
Confusion Matrix: The model correctly classified 7390 instances of Class 1 and 1530 instances of Class 0, with minimal misclassifications (40 false positives and 56 false negatives).

Precision and Recall involve two classes, 0 and 1:

Class 0: Precision and recall values of 0.96–0.97 indicate reliable identification of this class with minimal false alarms and missed detections.

Class 1: Both metrics were near 0.99, reflecting excellent performance in recognizing the dominant class.

Table 2: Model Performance Metrics: Validation and Test Loss/Metrics at Epoch 15.

Epoch/ Steps	Metrics
Trial 5 Complete [00h 02m 44s]	val_mae: 0.0081, Best val_mae So Far: 0.0081 Total elapsed time: 00h 20m 37s
902/902 7s 8ms/step	**loss:** 7.5623e-04 - mae: 0.0165 - val_loss: 4.9331e-04 - val_mae: 0.0109 **loss:** 4.5945e-04 - mae: 0.0083
282/282 1s 3ms/step	**Test Loss**: 0.00046, Test MAE: 0.00825
282/282 1s 3ms/step	Test Loss: 0.00046, Test MAE: 0.00825 RMSE: 0.021449, MAPE: 77.99 R-Squared:0.983479
282/282 1s 2ms/step	Accuracy: 0.989 and F1 Score: 0.993
282/282 1s 2ms/step	Classification Report: precision recall f1-score support 0 0.96 0.97 0.97 1570 1 0.99 0.99 0.99 7446
282/282 1s 2ms/step	

The following figures and analysis are described as:

Figure 5 involves training and validation loss over epochs showing effective training, with consistent loss reduction and minimal divergence between training and validation losses after convergence. This indicates strong generalization and robustness without overfitting.

General Trend: Training loss steadily decreases across epochs, while validation loss initially declines, confirming the model's effective learning.

Convergence: By epoch 8, both losses stabilize with minimal divergence, indicating well-balanced accuracy and generalization.

Validation Loss Fluctuations: Slight fluctuations in early epochs (e.g., between epochs 2–4) suggest weight adjustments for better generalization.

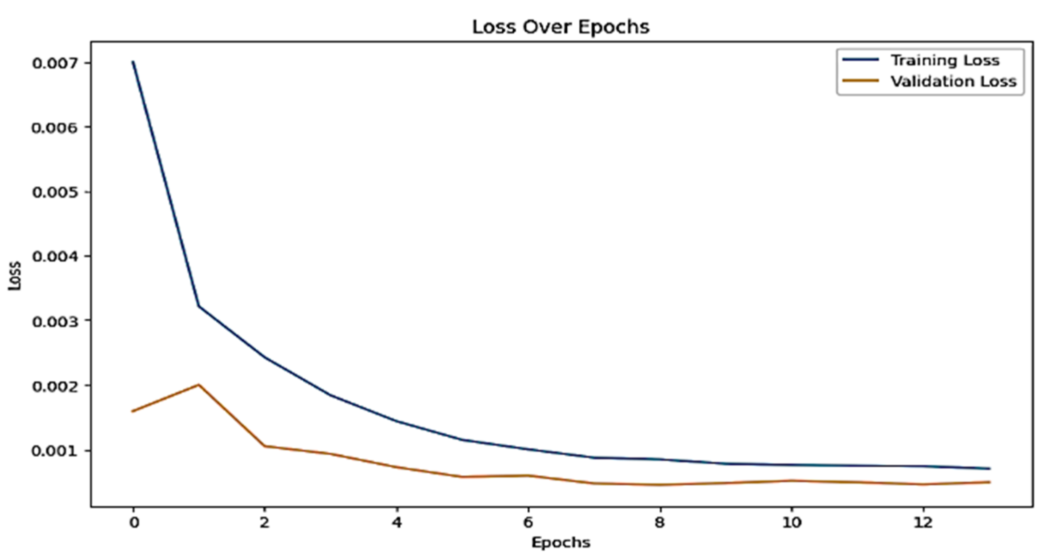


Figure 5: Training and Validation Loss Convergence Over Epochs.

Figure 6: The comparison of true versus predicted values shows a significant overlap, demonstrating the model's ability to capture data patterns effectively. The Figure shows a comparison between the true values (blue line) and the predicted values (orange line) generated by the model. The horizontal axis represents the data samples, while the vertical axis corresponds to the normalized values of the target variable.

The predicted values align closely with the true values, with minor deviations suggesting areas for improvement. Overall, the model performs consistently across the dataset without bias toward specific value ranges.

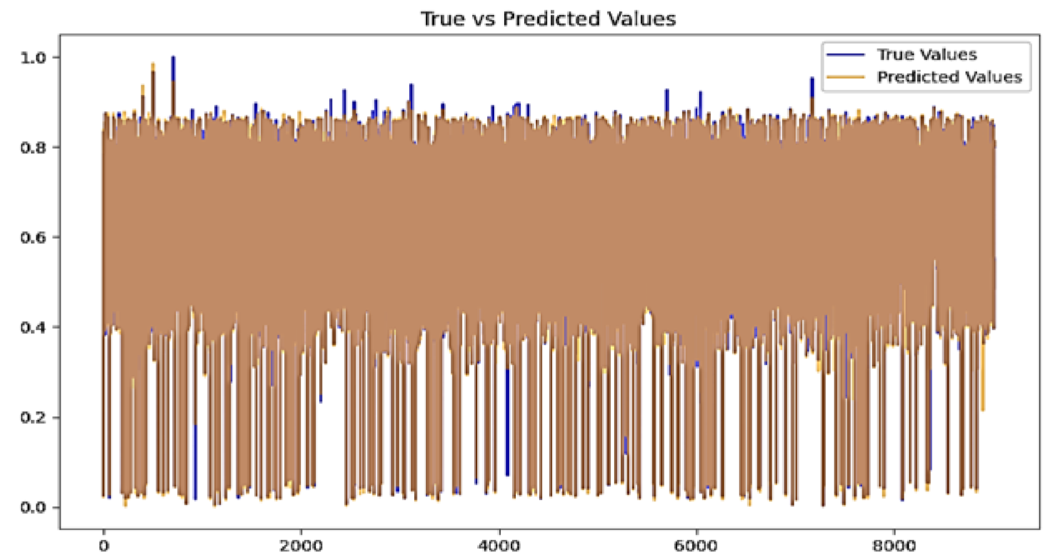


Figure 6: Comparison of True vs Predicted Values.

The proposed model in Table 3 achieves a classification accuracy of 98.93%, outperforming prior work and demonstrating its effectiveness for real-time recognition of neck posture using IMU sensors.

Table 3: Comparison with Similar Work.

Paper	Accuracy	Main Insights	Dataset
Camboim *et al.*[27]	---	Emphasis on reliable data for health applications	Various datasets
Tilili *et al.*[28]	85%	Real-time detection of bad posture using IMU sensors	Custom datasets
Patiño *et al.*[29]	90%	Real-time feedback on textile sensors	Daily activities Measurements
Low *et al.*[30]	88%	Effective for rehabilitation and ergonomic assessments	(IMU) generated by monitoring subjects
Wang *et al.*[25]	0.92 and 0.94	CNN for IMU-based movement analysis.	IMUs
Li *et al.*[26]	97.78%	CNN-based neck movement analysis	(IMU) to capture neck movement angles and velocities
Proposed	**98.93%**	High accuracy in real-time recognition	IMU to capture neck movement angles and velocities

To enhance the study's validity, we conducted a comparative analysis by evaluating additional deep-learning models alongside the LSTM, which is well-suited for time-series prediction. Experimental results in Table 4 indicate that LSTM surpasses both CNN and GRU, supporting its selection for this study. CNN Model: Convolutional layers effectively extract spatial patterns; however, CNNs struggle with preserving long-term temporal dependencies in sequential data. GRU Model: As a streamlined variant of LSTM, GRUs offer reduced computational overhead but may compromise detailed temporal representations. LSTM Model: Designed to retain long-range dependencies, LSTMs are particularly effective for prolonged posture monitoring.

Table 4: Shows the Comparative Performance of CNN, GRU, and LSTM Models.

Model	Accuracy	MAE	RMSE	R-Squared
CNN	0.88	0.123	0.25	0.85
GRU	0.9	0.117	0.22	0.88
LSTM	**98.93%**	0.008	0.021	0.983

Discussion

Although the proposed LSTM model demonstrates strong accuracy in predicting neck posture, several practical challenges must be considered for real-world implementation. One major concern is privacy, as continuous posture monitoring with IMU sensors could involve collecting sensitive data. Another challenge is user adherence, as individuals may be reluctant to wear sensors for prolonged durations. Additionally, enhancing the durability and comfort of wearable devices is essential to promote long-term usage. Future research should prioritize developing solutions that are both user-friendly and privacy-conscious to address these issues effectively.

Conclusions

Factors such as head weight and bending duration significantly influence the body's bending process and overall performance. Understanding the impact of these factors and implementing the suggested recommendations can enhance movement efficiency and help reduce the risk of movement-related injuries, including conditions like text neck syndrome, characterized by symptoms such as muscle spasms and tension in the neck and head. This research highlights the significance of head weight and bending duration as key factors affecting human body performance during bending activities. The term "time" in this context may refer to either sequential timing or specific periods of activity.

To maximize efficiency and minimize risks, these factors should be integrated into risk assessment protocols and intervention strategies. Considering these factors during training and implementation will refine risk management approaches and improve applicability in maintaining healthy work environments. This can lead to better injury prevention and enhanced overall well-being. Future research should focus on tackling the ethical and practical challenges associated with AI-powered posture monitoring systems, such as privacy issues, user adherence, and device reliability. Addressing these factors is essential for effectively integrating such systems into healthcare, workplace ergonomics, and sports training environments.

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