

An intelligent wearable system for skiing posture analysis and fall risk prediction based on physical modeling and neural networks

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Abstract. The sport of alpine skiing includes rapid body movements under changing terrain conditions, which can lead to falls and related injuries. This study presents a wearable sensing system designed to monitor skier posture and estimate fall risk in real time. The system gathers motion and plantar pressure information through two inertial measurement units installed on the shank and boot shaft, together with a pressure insole placed inside the boot. A rigid body model based on physical principles processes these sensor signals to calculate edge forces, edge angles, turning torques, and an overall stability index. A convolutional feature extraction module combined with a bidirectional Long-Short-Term Memory (LSTM) temporal network is used to classify posture into four risk states, including stable carving, excessive forward lean, backward imbalance, and fall-prone posture, while also generating a continuous risk score. Feedback is provided through visual warnings on a head mounted display, vibration cues from haptic devices, and a mobile application. The study also introduces the coordinate system definitions, rigid body force analysis, dynamic equations related to edge mechanics, and the Convolutional Neural Network-Bidirectional Long-Short-Term Memory (CNN BiLSTM) model structure used for real time prediction.

Keywords: alpine skiing, wearable sensing, rigid body dynamics, edge mechanics, fall prediction, convolutional neural network, bidirectional LSTM, stability index

1. Introduction

Alpine skiing combines high movement speed, uneven terrain conditions, and coordinated body control. Reported injury rates in recreational skiing are about two to four cases per thousand skier days, with falls representing a major cause of injury [1]. Knee ligament damage, wrist fractures, and head injuries account for a notable share of skiing related hospital admissions [2]. For this reason, reducing falls is an important aspect of injury prevention. Wearable sensing methods have been studied in multiple sports for monitoring movement and identifying potential risks. Inertial measurement units have been applied in snowboarding, speed skiing, and slalom skiing to evaluate posture and joint loading characteristics [3]. Many existing studies rely on offline analysis of collected data, while fewer systems focus on estimating fall risk during activity. Real-time feedback systems may support posture adjustment before loss of balance occurs.

Physics based modeling provides one method for deriving biomechanical variables from sensor measurements. In alpine skiing, the interaction between ski edges and the snow produces forces related to turning and balance control. Edge force and edge angle can describe aspects of skier dynamics that are associated with fall risk [4]. Neural network methods provide another approach for posture recognition and risk estimation [5]. These models can learn relationships between sensor signals and risk states without requiring a complete analytical description of body configurations. Convolutional encoders can extract local temporal features from input signals, while recurrent models are suitable for representing longer sequential dependencies [6]. Bidirectional LSTM networks analyze temporal information in both directions, which supports sequence modeling in offline evaluation and can also be adapted for online inference through streaming methods.

This study presents a system that combines these methods within a five-stage framework. A physics-based module computes edge mechanics features according to Newton Euler dynamics. A CNN BiLSTM model then processes both structured features and raw sensor data to classify posture states and estimate fall risk in real time. Feedback is provided through a visual display integrated with ski goggles, wrist worn haptic devices, and a mobile application.

2. System architecture

The proposed system consists of five stages, including sensing, data processing, physics-based modeling, neural network prediction, and risk evaluation with feedback. Figure 1 presents the overall system architecture.

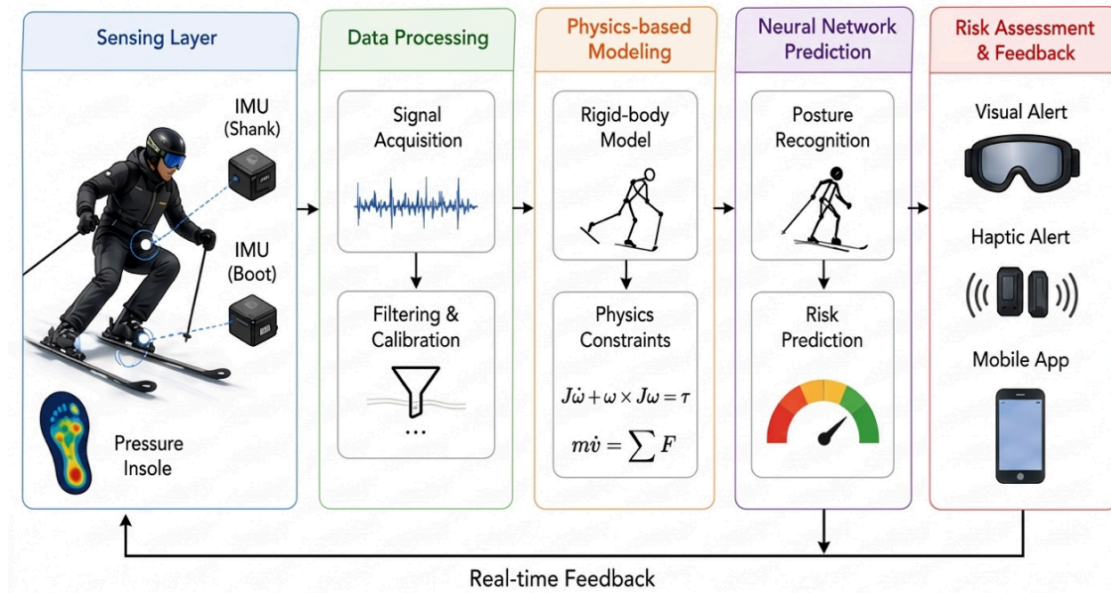


Figure 1. Overall system architecture. sensor signals from the IMUs and pressure insole pass through data processing and physics-based modeling before entering the neural network prediction stage

The proposed intelligent wearable system is structured as a multilayer framework that integrates sensing, data processing, physics-based modeling, neural network prediction, and risk feedback for real time monitoring of skiing posture and assessment of fall risk. At the sensing stage, biomechanical information is collected using two six axis inertial measurement units and a plantar pressure insole, with one IMU mounted

on the lower leg shank and the other fixed on the ski boot shaft to capture lower limb motion and ski boot interaction, while the insole records plantar pressure distribution. The acquired signals are then synchronized, filtered, and calibrated, where a bandpass filter is applied to reduce low frequency drift and high frequency noise in the inertial data and the pressure maps are normalized and resampled to match the inertial sampling rate for multimodal fusion. Based on the processed data, a physics-based modeling module uses a rigid body formulation governed by Newton Euler equations to estimate variables such as edge force, edge angle, and turning torque, which are combined with the raw signals as inputs for the prediction stage. The prediction module adopts a CNN BiLSTM architecture in which a convolutional encoder extracts feature representations and a bidirectional LSTM models temporal dependencies, followed by two parallel output branches that classify posture into four risk categories and compute a continuous fall risk score. The resulting estimates are then used in a feedback stage where visual alerts are shown on a goggle mounted display, haptic signals are delivered through wrist worn vibration devices, and a mobile application stores session data and provides post run summaries, forming a closed loop system for skiing safety monitoring.

The hardware is implemented as a self-contained module mounted on the ski boot, integrating sensing and computation units in one unit. Figure 2 presents an exploded view of the boot structure, the placement of sensors on the lower limb, and an image of the assembled prototype.

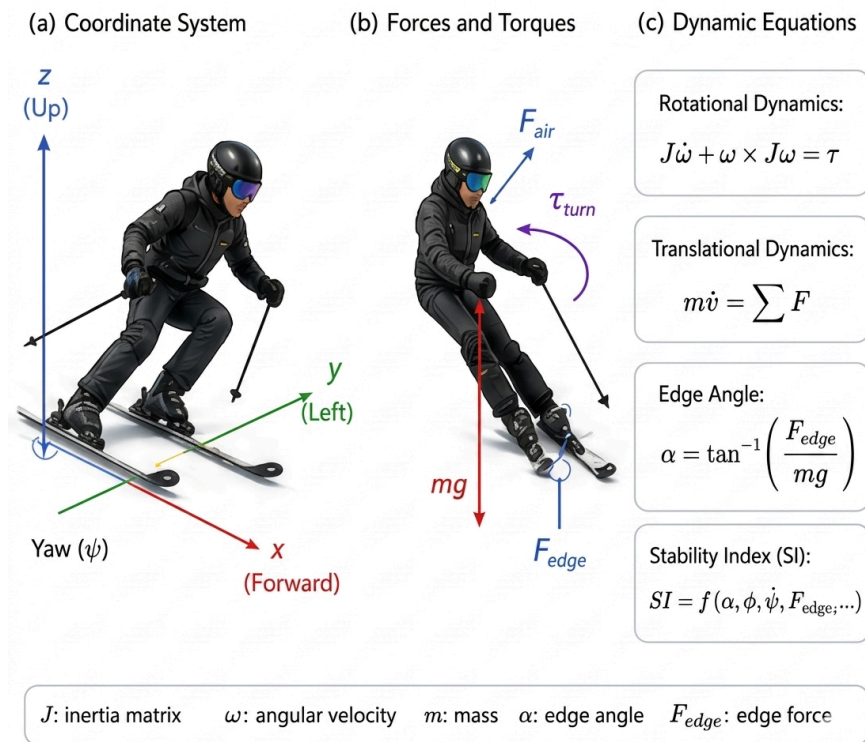


Figure 2. Hardware design. (a) exploded view showing the upper shell, shank IMU module, strap, control unit with battery, pressure insole, haptic motor, and boot sole. (b) sensor placement: IMU at the shank, IMU at the boot shaft, and pressure insole inside the boot. (c) photograph of the assembled prototype

The upper shell is designed to clip onto the boot cuff and holds the shank IMU in a fixed alignment with the lower leg axis. A fastening strap is used to keep the module stable and to reduce rotation during movement. The control electronics and battery are placed on the lateral side of the boot in a recessed position, which helps

limit interference with the binding area. The pressure insole is inserted inside the standard liner and is connected to the control unit through a shielded flat cable that runs along the inner side of the boot.

A vibration motor is integrated into the sole under the heel to provide low frequency haptic output that can be perceived through the liner while remaining distinguishable from vibration caused by skiing terrain. The full system adds about 68 grams to the boot and does not require permanent changes to the equipment. All components are specified to operate within a temperature range from minus 20 degrees Celsius to 50 degrees Celsius, which covers common alpine skiing conditions.

3. Physics-based modeling framework

In the physics model, raw IMU and pressure measurements are transformed into biomechanically meaningful variables that describe the skier's motion state. Figure 3 illustrates the body-fixed coordinate system and the principal mechanical quantities used in the physical modeling framework, including the edge reaction force, aerodynamic drag, turning torque, yaw angle, and edge angle.

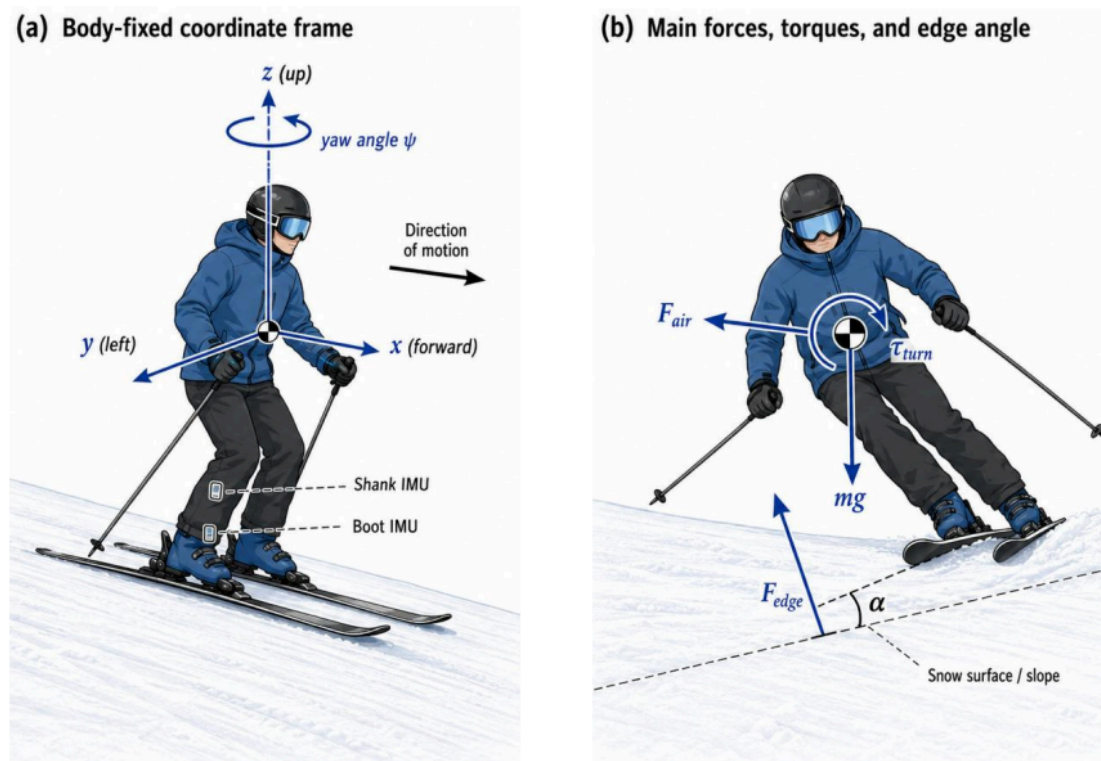


Figure 3. Coordinate frame and physical force model for skiing posture analysis

3.1. Coordinate frame definition

A body fixed reference frame is defined on the skier, with the x axis oriented forward along the direction of motion, the y axis directed to the left side, and the z axis aligned upward along the body. This definition follows a standard convention used in rotational dynamics. The yaw angle ψ represents rotation about the vertical axis and is used to describe the turning direction during skiing [7]. The shank mounted IMU records angular velocity and linear acceleration, and its measurement frame is aligned with the body fixed frame through a calibration step performed when the skier is stationary on a level surface [8].

3.2. Forces and torques

Four principal forces and torques act on the skier during a carved turn. The gravitational force mg acts vertically downward, where m is the total body mass and g is the gravitational acceleration. The edge reaction force F_{edge} acts perpendicular to the ski base and is the primary force opposing the lateral component of gravity during a turn; it is estimated from the plantar pressure distribution and the IMU measurements at the boot. The aerodynamic drag force F_{air} acts in the direction opposing forward motion and is approximated as a function of the square of the estimated speed. The turning torque τ_{turn} represents the net moment about the skier's center of mass that drives the change in yaw during a carved arc.

3.3. Rotational dynamics

The rotational dynamics of the skier's body are governed by the Newton–Euler equation for a rigid body rotating under an applied torque:

$$J\dot{\omega} + \omega \times J\omega = \tau \quad (1)$$

where J is the inertia matrix of the body segment, ω is the angular velocity vector measured by the IMU, $\dot{\omega}$ is the angular acceleration estimated by numerical differentiation, and τ is the net torque vector. The term $\omega \times J\omega$ is the gyroscopic coupling term that accounts for the redistribution of angular momentum as the segment rotates. Angular velocity measurements from the shank IMU are used directly in this equation. The inertia matrix J is estimated from standard biomechanical tables parameterized by body mass and height [9].

3.4. Translational dynamics

The translational dynamics follow Newton's second law applied to the whole-body center of mass:

$$m\ddot{y} = \Sigma F \quad (2)$$

where m is the total body mass, $\ddot{y}$ is the linear acceleration of the center of mass, and ΣF is the vector sum of all external forces. By integrating the accelerometer measurements from both IMUs and correcting for gravitational acceleration using the current orientation estimate, the system reconstructs the net external force acting on the body at each time step. This quantity, together with the gravitational component, allows the edge force F_{edge} to be decomposed from the total contact force measured by the pressure insole.

3.5. Edge angle

The edge angle α describes how much the ski is tilted relative to the snow surface and reflects the level of engagement during a carving turn. It is computed as the inverse tangent of the ratio between the edge force and the component of gravitational force acting normal to the slope:

$$\alpha = \tan^{-1}(F_e^{dge}/mg) \quad (3)$$

Larger values of the edge angle correspond to a strongly carved turn with higher lateral load on the ski. While this condition can improve turning efficiency, it also reduces the margin for regaining balance once instability begins. Smaller or negative edge angles suggest insufficient edging, which is often associated with skidding and reduced control over the skiing direction. As a result, the edge angle can be used as an early signal of changes in stability that may lead to a fall.

3.6. Stability index

The stability index SI synthesizes multiple mechanical indicators into a scalar quantity that summarizes the overall balance state of the skier at each time step:

$$SI = f(\alpha, \dot{\varphi}, \dot{\psi}, F_{edge}^{dg}, \dots) \quad (4)$$

where α is the edge angle, $\dot{\varphi}$ is the roll rate, $\dot{\psi}$ is the yaw rate, and F_{edge} is the edge force magnitude. The function f is formed as a weighted linear combination of the selected variables, where the weights are learned through supervised regression using labeled training data. This stability index provides a compact representation of the skier's state and is used together with raw sensor measurements and physics-based features as input to the neural network. When the index falls below a predefined threshold obtained through calibration, it is treated as an independent early warning signal. This rule offers a physics-based reference in addition to the neural network output.

4. Neural network for posture classification and risk prediction

The neural network uses two input streams, one from IMU signals and the other from pressure maps. Both streams are first processed by a shared convolutional encoder to extract feature representations. The encoded features are then passed into a bidirectional LSTM to model temporal relationships in the data. After this stage, two separate output branches are used, one for posture classification and the other for continuous risk estimation. Figure 4 presents the full network structure.

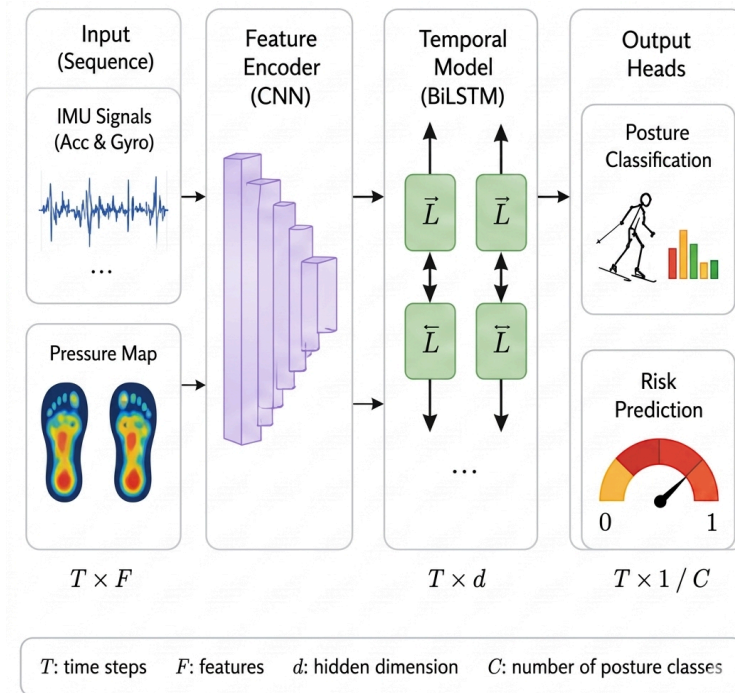


Figure 4. Neural network architecture. IMU acceleration and gyroscope signals and the plantar pressure map are encoded by a CNN feature encoder into a $T \times d$ representation, which is processed by a BiLSTM temporal model. one output head classifies posture into C categories; the other produces a continuous risk score in $[0, 1]$

4.1. Input feature representation

At each time step t , the network takes in two synchronized input streams. The first stream contains inertial measurements from the two IMUs, including three axis accelerometer data and three axis gyroscope data from both the shank and the boot units, resulting in a twelve-dimensional vector for each time step. In addition, physics-based variables such as the edge angle α , stability index SI , and estimated edge force magnitude are concatenated to form the complete inertial feature set. The second stream consists of pressure information from the insole, which is expressed as a two-dimensional spatial grid and resampled to a fixed resolution. Both streams are organized as sequences over T time steps, forming an input tensor with dimensions T by F , where F represents the total number of features.

4.2. Convolutional feature encoder

A one-dimensional convolutional neural network is applied to the feature vector at each time step to capture local temporal patterns. The encoder consists of several convolutional layers with progressively more filters and smaller kernel sizes, and each layer is followed by batch normalization and a ReLU activation function. The pressure map input is handled by a separate two-dimensional convolutional branch, which reduces the spatial dimensions before merging with the inertial feature stream. After encoding, the original input of size T by F is mapped into a hidden representation of size T by d , where d denotes the hidden feature dimension. The temporal structure is maintained so that the bidirectional LSTM can further learn dependencies across the full sequence window.

4.3. Bidirectional LSTM temporal model

The convolutional features with dimensions T by d are input to a bidirectional LSTM composed of two layers. Each layer includes a forward LSTM and a backward LSTM with the same hidden size, and their outputs are combined at every time step by concatenation. The use of both directions allows the model to utilize information from the entire input window when analyzing balance conditions that change over time. In online operation, only the forward LSTM direction is used as an approximation, which introduces a delay related to roughly half of the window length when compared with the center of the sequence. The resulting T by d representation from the BiLSTM is then fed separately into the two output branches.

4.4. Output heads

The posture classification head uses a linear layer to project the features, and a softmax function is applied to produce probabilities over C posture categories. Figure 5 presents the four posture categories identified by the system, along with example photographs and corresponding stick figure skeletal representations.

The system defines four posture categories, including stable carving, excessive forward lean, backward imbalance, and fall prone posture. The risk prediction branch uses a linear layer followed by a sigmoid function to generate a continuous value between 0 and 1, which is interpreted as the probability of a fall occurring within the next 500 ms. This two-output structure provides both a discrete classification result for basic alerting and a continuous risk score that can be used to adjust the level of feedback provided by the system.



Figure 5. Posture categories and associated risk levels

4.5. Training protocol

The network training uses a combined loss function that includes a cross-entropy component for posture classification and a binary cross entropy component for fall risk prediction, with the two parts assigned to the same weight. Optimization is performed using the Adam algorithm, starting from a learning rate of 0.001, which is reduced by a factor of 0.5 when the validation loss does not improve over five consecutive training epochs. A dropout rate of 0.3 is applied between LSTM layers to reduce overfitting. To address class imbalance, weighting factors are introduced in the cross-entropy loss because stable carving accounts for most of the recorded skiing data. Fall events and the 500 ms interval before each labeled fall are marked as fall prone samples for the classification task and as positive samples for the risk prediction task. Table 1 summarizes the key parameters used in the system configuration and training setup.

Table 1. Key parameters of the system

Parameter	Value
IMU sampling rate	200 Hz
Pressure insole rate	100 Hz
Physics model update rate	200 Hz
Inertial feature dimension	15 per step (12 IMU + 3 physics)
Pressure map resolution	16 × 4 spatial grid
Input window length T	50 steps (250 ms)
CNN hidden dimension d	128
BiLSTM layers / units	2 / 128 (each direction)
Posture classes C	4 (stable, forward lean, backward, fall-prone)
Dropout rate	0.3
Fall risk threshold	0.65
Processing latency target	< 80 ms

5. Feedback interface and deployment

The system is designed to keep the total processing delay from sensor acquisition to feedback output below 80 ms. Risk information is provided through three parallel channels. The visual interface mounted on the ski goggles displays a color-coded risk level updated at 25 Hz. The mapping assigns green to stable carving, amber to excessive forward lean, orange to backward imbalance, and red to the fall prone state. The wrist worn haptic units generate vibration patterns that represent different risk levels. A single pulse of 50 ms indicates moderate risk, a repeated pulse of 100 ms indicates high risk, and continuous vibration corresponds to the highest risk level. When the risk score exceeds 0.65 for three consecutive inference cycles, the vibration of intensity is increased. A mobile application receives data through Bluetooth Low Energy and records posture labels, risk scores, and GPS coordinates for later review. The hardware is implemented as a modular device mounted on the ski boot with a total mass of 68 grams and does not require permanent changes to the boot. Communication between the two boot mounted units and the mobile application is handled through a Bluetooth mesh network with a typical range of about 20 meters.

6. Discussion

Several limitations of the current approach can be identified. The stability index SI is constructed as a weighted linear combination of physics-based features, where the weights are obtained through supervised regression on the training data. This design may not transfer well to skiers whose movement patterns differ from those represented in the dataset, especially in very high or very low skill groups. A learned stability measure based on the data could reduce this issue, although it would reduce interpretability compared with the current formulation.

The estimation of edge force assumes that the pressure insole captures the full ground reaction force transmitted through the boot. In real use, part of the force can be transferred through the boot cuff to the lower leg, particularly during forward leaning postures. This component is not measured by the insole, which may lead to underestimation of the edge force in such cases. This condition is related to the excessive forward lean class, which is important for system detection performance.

The bidirectional LSTM makes use of future information within the input window, which results in an effective delay equal to about half of the window's length, or approximately 125 ms when evaluated offline. In online use, the model is simplified to a causal form that removes the backward pass, enabling real time operation. This change may reduce sensitivity to short instability patterns that appear before a fall. A comparison between offline and online performance is needed for further evaluation.

The feedback system uses three channels, including visual, haptic, and mobile output, to support different usage conditions during skiing. The mapping between risk levels and feedback signals has not yet been evaluated in user testing. Repeated warnings at the moderate risk level may lead to reduced attention to alerts over time. Further studies on user response and alert frequency are required to adjust the threshold settings.

7. Conclusion

This paper presents an intelligent wearable system for analyzing skiing posture and estimating fall risk. The approach combines a physics-based rigid body model with a CNN BiLSTM network. The physics module derives variables such as edge force, edge angle, turning torque, and a stability index from measurements collected by two IMUs and a pressure insole. These features are then used by the neural network to classify posture into four risk levels while also generating a continuous risk score. The system is organized as a five-

stage pipeline covering sensing, data processing, physics-based modeling, neural network inference, and risk assessment with feedback. The overall processing is designed to operate within an 80 ms latency constraint. Output information is provided through a goggle mounted visual interface, wrist worn haptic devices, and a mobile application. The dynamic equations used in the model, together with the definition of edge angle and the stability of index formulation, provide a physically interpretable basis for the input features. Future work includes validation under outdoor skiing conditions with participants of different skill levels and further adjustment of feedback thresholds through controlled user studies.

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