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Plantar Pressure Distribution in Novice Roofers: Effects of Slope and Posture with ML-Based Classification

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ABSTRACT: Construction roofers face hazardous environments due to their activities at sloped and uneven surfaces, carrying heavy loads, and awkward postures. These postures increase musculoskeletal risks, particularly for novice roofers who struggle to balance their weight distribution on slopes. However, research on plantar pressure distribution among novice roofers remains limited. The study examines the effects of the roof slopes (0°, 15°, 30°) on plantar pressure distribution across foot zones (toe, metatarsal, midfoot, heel) during kneeling, standing, and stooping to identify high-risk areas and evaluate machine learning methods for pressure data classification. High-risk zones were identified based on statistically significant increases in peak pressure values ($p < 0.05$), indicating greater biomechanical load and potential musculoskeletal strain. Eight novice participants simulated shingle installation on a sloped wooden mock-up in a laboratory setting. The study used ANOVA to analyze plantar pressure distribution of peak pressure across various foot zones at different slopes by using XSensor pressure insoles. Three-way ANOVA was conducted to statistically analyze the effects of posture, slope angle, and foot zone on peak pressure. 5 Further, four machine learning models – Random Forest, Decision Tree, Support Vector Machine, and K-nearest neighbors were applied for the classification. The results indicate posture significantly affects plantar pressure. Among machine learning models, Random Forest achieved the highest accuracy (training: 92%, test: 91%), demonstrating its strength in handling non-linear relationships and high-dimensional data. This study advances roofing ergonomics by quantifying plantar pressure variations on inclined surfaces, identifying high-risk foot zones for musculoskeletal disorders, and showcasing machine learning's potential for automated posture classification. These findings can inform safer work practices and ergonomic interventions for novice roofers.

1. INTRODUCTION

1.1 Background

Roofing is a physically demanding occupation requiring workers to maintain stability on inclined surfaces, often in awkward postures such as stooping, kneeling, and squatting for prolonged periods. These postures lead to uneven plantar pressure distribution, increasing the risk of fatigue, instability, and musculoskeletal disorders (MSDs). Research highlights that low back disorders (LBDs) are prevalent among roofers, exacerbated by factors such as posture, roof slope, and working pace (Wang et al., 2015; Wang et al., 2017). The top three musculoskeletal pain (MSPs) for roofers were foot, back, and knee (Kisi & Kayastha, 2024) which were also contributing factors to fall accidents among Hispanic construction workers (Kayastha & Kisi, 2024). Unlike experienced workers who intuitively adjust to slopes, novices often experience elevated pressure in the forefoot zones (toes and metatarsals) due to the multiple contributing factors. The contributing factors might be imbalance, and a tendency to lean forward or shift their center of mass toward the toes when navigating inclined surfaces. Additionally, novices typically lack training on optimal foot placement and weight redistribution strategies during their entry-level work since they are exposed to the tasks without or with less experience. This imbalance highlighted in recent construction safety studies by Choi et al. (2016). Studies suggest that postural imbalances and improper weight shifts significantly impact worker safety and performance, with roofers spending up to 75% of their working time in awkward positions (Dutta et al. 2020).

1.1.1 Plantar Pressure Measurement System

Plantar pressure measurement systems, such as Xsensor, are widely used in occupational biomechanics to assess foot pressure distribution during various postures and activities (Parker et al. 2023). These high-resolution sensor-based technologies provide critical insights into weight distribution and postural stability, and food deformity (Cudejko et al., 2023). While these systems effectively quantify peak plantar pressures across different foot zones, their integration with machine learning for real-time posture classification remains underexplored.

1.1.2 Biomechanical Challenges in Roofing Postures

Roofing postures, such as stooping, kneeling, and walking on sloped surfaces, pose significant biomechanical challenges, including balance loss, improper weight distribution, and increased lower extremity strain (Breloff et al., 2020). Studies indicate that postural imbalances contribute to fatigue, discomfort, and heightened fall risk in construction workers (Wong et al., 2016). These risks are amplified in novice roofers, who require ergonomic interventions to improve stability and reduce musculoskeletal strain (Garcia et al., 2023). However, current interventions fail to account for plantar pressure variations across different foot zones on inclined surfaces, limiting their effectiveness in real-world applications.

1.1.3 Machine Learning for Posture Recognition

Machine learning has emerged as a powerful tool for posture classification and risk assessment, with models such as Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), and K-Nearest Neighbor (KNN) demonstrating high accuracy in plantar pressure analysis (Antwi-Afari et al. 2018). However, their integration with wearable sensor technology for real-time posture monitoring in roofing remains less explored.

DT is an interpretable and effective model for small datasets but is prone to overfitting (Bishop & Nasrabadi, 2006). RF enhances DT by employing ensemble learning, improving generalization and accuracy, particularly for high-dimensional data, though it demands higher computational resources (Breiman, 1984; Wang et al., 2017). KNN is beneficial for non-linear classification but becomes computationally expensive for large datasets and is sensitive to irrelevant features (Akhavian & Behzadan, 2016; Pradhan et al., 2015). SVM uses kernel-based classification, making it highly effective for small, high-dimensional datasets, but it requires fine-tuning for optimal performance (Debnath et al., 2004).

While classifier effectiveness depends on the characteristics of the dataset, feature quality, and task complexity, Random Forest has demonstrated strong generalization ability in plantar pressure-based classification tasks in recent studies (e.g., Antwi-Afari et al., 2018; Li et al., 2024). Its robustness to noise and ability to handle non-linear relationships make it a favorable choice for complex biomechanical data. However, its performance shall be evaluated contextually rather than assumed universally.

1.1.4 Summary of Key Findings & Research Gap

While several studies have explored the biomechanical challenges of roofing tasks, most have focused on either experienced workers or isolated aspects of the body, such as knee muscle activation or trunk kinematics during shingle installation on sloped roofs (Pan et al., 2009; Dutta et al., 2020; Breloff et al., 2022). Similarly, extensive research has explored plantar pressure distribution in general construction tasks, there is a notable lack of studies focusing on the effect of slope angles on novice roofers who frequently work in unstable and awkward postures. For example, Previous studies, such as Choi et al. (2016) and Antwi-Afari et al. (2018), primarily examined pressure patterns in experienced workers or under controlled, level-ground conditions, assuming participants were able to self-adjust their postures. Similarly, Existing research primarily examines overall pressure shifts but fails to analyze individual foot zone responses under varied postures and incline conditions. This limits our understanding of how specific foot regions adapt to increased biomechanical demands on sloped surfaces, which is critical for injury prevention and ergonomic intervention development.

Additionally, while machine learning has been applied to posture classification, its integration with wearable sensor technology for real-time plantar pressure analysis in roofing environments remains underexplored. Roofers spend approximately 75% of their working hours in awkward positions (Dutta et al. 2020), increasing their susceptibility to musculoskeletal disorders (MSDs) and fall risks. Current studies often overlook dynamic weight distribution, fatigue effects, and postural adjustments that occur during prolonged roofing tasks. The unique challenges faced by novice roofers—such as inconsistent weight shifting, poor balance, and unfamiliarity with slope adaptation remain unexplored. This study, therefore, aims to bridge these gaps by analyzing plantar pressure distribution across foot zones and postures on inclined surfaces while evaluating machine learning models for accurate classification and risk assessment. The findings will contribute to ergonomic solutions, adaptive footwear design, and AI-driven injury prevention strategies, enhancing workplace safety and reducing fall risks in roofing and other high-risk occupations.

1.2 Problem Statement

There is a lack of understanding regarding how different roof slopes impact plantar pressure distribution and postural stability, particularly among novice roofers. This knowledge gap leads to an increased risk of instability, fatigue, and long-term MSDs. Current ergonomic interventions are not sufficient to address real-time biomechanical risks across foot zones under varying slopes using plantar pressure distribution, nor do they leverage machine learning for automated risk assessment. Addressing these issues is crucial for enhancing occupational safety, designing better footwear, and reducing injury risks.

1.3 Objectives

1. Analyze the effects of roof slopes (0°, 15°, 30°) on plantar pressure distribution
2. Identify foot zones with the highest peak pressures to assess discomfort and injury risks.
3. Evaluate machine learning models (RF, SVM, DT, KNN) for classifying plantar pressure patterns to enhance predictive foot biomechanics analysis.

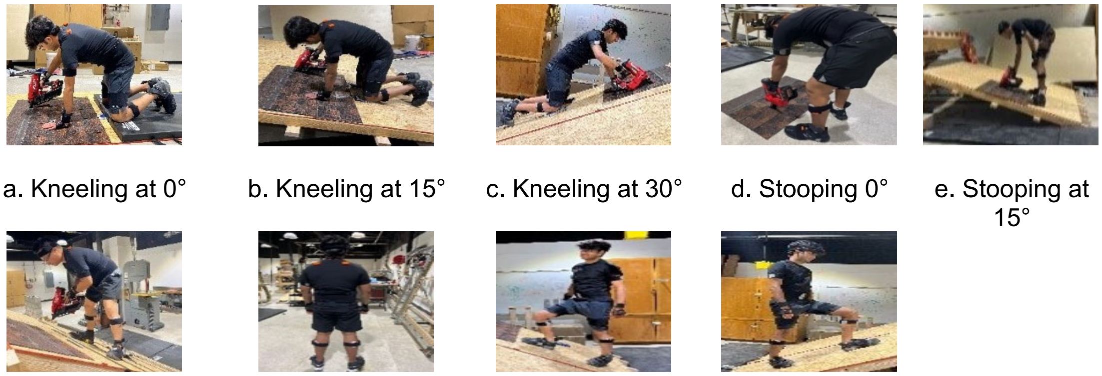
1.4 Research Significance

This study provides data-driven insights into plantar pressure dynamics, including adaptive footwear and injury prevention strategies, aiding in ergonomic intervention development. Integrating machine learning enables real-time monitoring using wearable sensors, improving workplace safety, stability, and health in high-risk occupations.

2. MATERIALS AND METHODS

2.1 Experimental Setup

The study used pressure-sensitive insoles called the intelligent insoles from XSensor company and used their Xsensor Pro Foot & Gait software to analyze plantar pressure distributions. The data were collected in a controlled environment with varied slope angles (0°, 15°, and 30°) and three postures (kneeling, stooping, and standing). The experiment setup is shown in Figure 1 below.



a. Kneeling at 0° b. Kneeling at 15° c. Kneeling at 30° d. Stooping 0° e. Stooping at 15°

f. Stooping at 30° g. Standing 0° h. Standing at 15° i. Standing at 30°

Figure 1. Kneeling, Stooping and Standing at 0°, 15° and 30° slopes

2.2 Participants

Eight male novice participants (mean age: 25 ± 5 years, mean weight: 70 ± 10 kg) were recruited. Recruited participants were free from prior foot injuries, chronic low back injury, ankle injuries, joint concerns or feet injuries that could affect gait or posture. The participants are students considered novice, who do not have prior experience or expertise in roofing or related construction activities or less than 3 months of work experience on roofing tasks. Sample size is smaller in this study due to the limitation of volunteering challenges and time-intensive nature of data collection logistical challenges, and safety considerations. Similar studies used less than ten sample sizes such as Breloff et al. (2019), Antwi-Afari et al. (2020), and Dutta et al. (2023). This study was conducted in accordance with ethical guidelines approved by the Texas State University Institutional Review Board (IRB). All participants provided written informed consent, including pre-screening consent and full informed consent, prior to participation.

2.3 Data Collection and Analysis

The pressure data was collected using Xsensor Pro Foot & Gait software. Each participant performed three postures (kneeling, stooping, and standing) for one minute each, with three repetitions per posture at slope angles of 0°, 15°, and 30°. The order of slopes was fixed (0° → 15° → 30°), and within each slope, the postures followed a fixed sequence. No rest periods were given between trials. The total testing duration per participants is 25 mins that includes setting up, walking trial, postural trials, and resting.

Each 1-minute trial yielded approximately 1,800 data points or frames (at 75 Hz). After removing the first and last 5 seconds to reduce noise, a 50-second segment was retained per trial. This resulted in a total dataset of approximately 129,600 data points (1,800 × 9 trials × 8 participants). The collected data satisfied the requirements for both Three-way ANOVA analysis—with at least 20 to 30 data points per group—and machine learning models, which typically require several hundred to a few thousand data points for reliable statistical inference. The significance level was set at $p < 0.05$. Partial eta squared () values were calculated to assess effect sizes.

Machine learning models used in this work include RF, SVM, Decision Tree, and KNN to classify plantar pressure data across different foot zones. These classifiers have demonstrated promising performance in the domain of human activity recognition and fall risk detection, as supported by previous studies (Akhavian and Behzadan, 2016; Antwi-Afari et al., 2018; Ryu et al., 2019).

3. RESULTS

3.1 ANOVA Procedures

The Shapiro–Wilk test and Q–Q plot inspections confirmed that plantar pressure data across postures, foot zones, and slope angles met the normality assumption ($p > 0.05$). Levene's test verified homogeneity of variances among groups. A between-subjects three-way ANOVA was conducted to assess the main and interaction effects of posture, foot zone, and slope angle on peak plantar pressure. When significant effects were observed ($p < 0.05$), post-hoc pairwise comparisons were performed using the Tukey–Kramer method. Partial eta squared (η^2) values were reported to indicate effect sizes. All statistical analyses were performed using IBM SPSS Statistics 27, with significance set at $p < 0.05$.

3.1.1 Statistical analysis (Three-way Anova results)

The ANOVA results in Table 1 indicate that posture has the strongest effect on peak pressure ($F = 156.36$, $p < 0.0001$, $\eta^2 = 0.2388$), highlighting significant pressure variations across different postures. Similarly, foot zones exhibit substantial differences in peak pressure ($F = 61.56$, $p < 0.0001$, $\eta^2 = 0.0940$), with specific regions experiencing higher pressure. The slope angle moderately influences peak pressure ($F = 4.11$, $p = 0.0428$, $\eta^2 = 0.0042$), indicating a small but noticeable impact of incline on foot loading.

Figure 2 illustrates the relationship between slope angle (0°, 15°, 30°) and peak pressure across different foot zones (Toe, Metatarsal, Midfoot, Heel). Peak pressure decreases initially from 0° to 15° and then shows variability at 30°. Both zones (Toe and Metatarsal Zones) experience higher peak pressure at 0°, which then drops at 15° before rising again at 30°. Midfoot Zone shows Shows a consistent decrease in pressure with increasing slope angle.

Table 1: Between-subjects effects (Three-way ANOVA results)

Source	Sum Sq	df	F	p-value	Partial Eta Squared
Posture	13298.58	3	156.35	0.0000	0.2388
Foot_Zone	5236.23	3	61.56	0.0000	0.0940
Slope_Angle	233.26	2	4.11	0.0428	0.0042
Posture x Foot_Zone	6169.53	9	24.17	0.0000	0.1108
Posture x Slope_Angle	1035.87	6	6.08	0.0024	0.0186
Foot_Zone x Slope_Angle	881.15	6	5.18	0.0004	0.0158
Posture x Foot_Zone x Slope_Angle	568.05	18	1.11	0.3451	0.0102

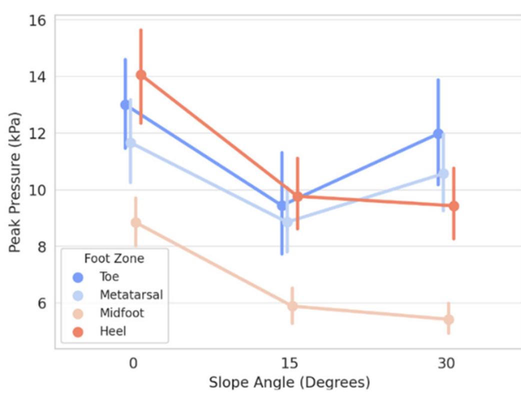


Figure 2: Peak Pressure vs Slope Angles and Foot Zones

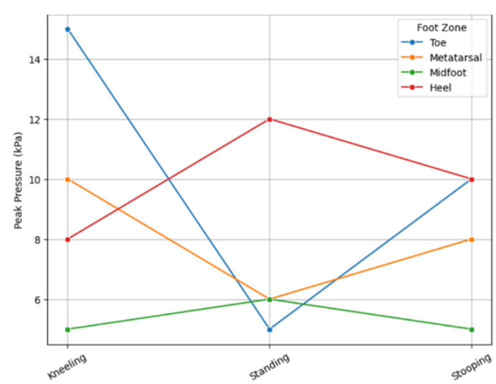


Figure 3: Interaction Plot of Posture and Foot Zones on Peak Pressure

3.1.2 Interaction effects

Significant interaction effects were observed between posture and foot zone ($F = 24.18$, $p < 0.0001$, $\eta^2 = 0.1108$), suggesting that pressure distribution is posture-dependent within different foot regions. According to Figure 3, kneeling exerts high pressure on the toes and moderate pressure on metatarsals but low on the midfoot and heel. Standing shows an inverse trend, with metatarsals carrying the highest pressure and toes, midfoot, and heels balancing the load. Stooping increases toe and metatarsal pressure again, resembling kneeling but with slightly more midfoot involvement. Heel pressure remains consistently low, indicating a forward weight shift in all postures except standing.

Additionally, posture and slope angle interact significantly ($F = 6.09$, $p = 0.0024$, $\eta^2 = 0.0186$), implying that postural adjustments are necessary when working on inclined surfaces. As shown in Figure 4, as a general trend, standing consistently shows the lowest peak pressure across all slope angles. Kneeling and Stooping exhibit higher peak pressures, with an increasing trend as the slope angle rises. As far as slope angle concerned, at 0° (flat surface), the pressure distribution across postures is moderate. As the slope angle increases to 15° and 30°, kneeling and stooping show a rise in peak pressure, suggesting increased strain in these postures. The highest peak pressure is observed for kneeling at 30°, indicating greater foot loading at steeper inclines.

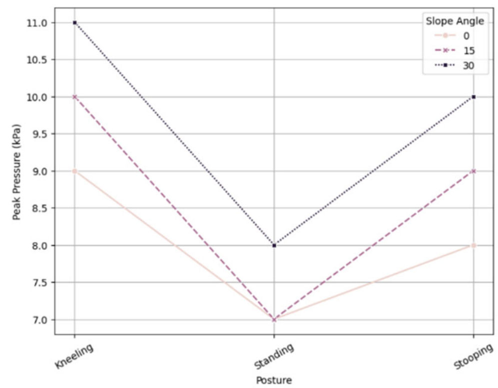


Figure 4: Interaction Plot of Posture and Slope Angle on Peak Pressure

The interaction between foot zone and slope angle is statistically significant ($F = 5.18$, $p = 0.0004$, $\eta^2 = 0.0156$), indicating that pressure distribution across foot zones changes with varying incline levels. → As the slope angle increases, pressure shifts away from the midfoot and redistributes more towards the metatarsal and toes, which may lead to increased discomfort in these regions.

The three-way interaction between Posture, Foot zone, and Slope angle is not statistically significant ($F = 1.11$, $p = 0.3451$, $\eta^2 = 0.0043$), suggesting that the combined influence of posture, foot zone, and slope angle does not create additional variability.

3.2 Machine learning performance

3.2.1 Data and machine learning workflow

All machine learning experiments were performed using Google Colab with Python libraries such as pandas, scikit-learn, and matplotlib. As illustrated in the flowchart, the process began with data cleaning (removing duplicates, missing values, and outliers), followed by data transformation through label encoding (All the categorical variables, Slope Angles, Foot Zones, and Postures) and MinMax normalization (Numerical features scaled to a [0,1]. In feature extraction and selection, the initial dataset included biomechanical features: minimum pressure, average pressure, peak pressure, estimated load, contact area, posture, slope angle, and foot zone. Feature importance evaluation was done by using ensemble tree method to identify the most relevant predictors, and posture, foot zone, slope angle and peak pressure (as the dependent biomechanical outcome) were selected for further modelling and interpretation. The processed data were then split into training and testing sets using an 80:20 ratio. Four classifiers—Decision Tree, Random Forest, SVM, and KNN—were trained and evaluated. Performance was assessed using accuracy, precision, recall, and F1 score.

3.2.2 Results Comparison

According to Table 2, Random Forest outperformed other models with a training accuracy of 92% and a test accuracy of 91%, making it the most effective classifier. Decision Tree had moderate performance, achieving 85% and 82% accuracy for training and testing datasets. SVM and KNN showed comparable accuracies (training: 89%, 88%; testing: 87%, 86%). This analysis highlights

Random Forest as the most reliable model for classifying plantar pressure data. As per Table 3, Random Forest performed best across all metrics (accuracy 90%, F1 score 90%), followed by SVM (87%), Decision Tree (85%), and KNN, which showed the lowest performance.

Table 2. Training and Test Accuracies

Model	Training Accuracy	Test Accuracy
Decision Tree	0.85	0.82
Random Forest	0.92	0.91
SVM	0.89	0.87
KNN	0.88	0.86

Table 3. Model Evaluation

Model	Accuracy	Precision	Recall	F1 Score
Decision Tree	0.85	0.86	0.84	0.85
Random Forest	0.9	0.91	0.89	0.9
SVM	0.87	0.88	0.86	0.87
KNN	0.83	0.84	0.82	0.83

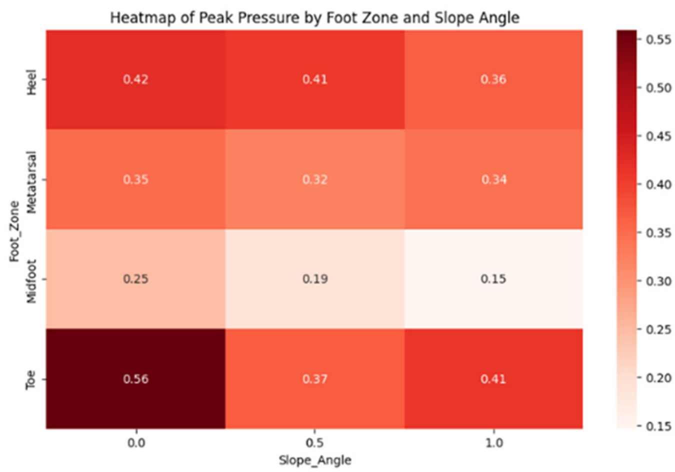


Figure 5: Heatmap of Peak pressure

Based on the information obtained from Figure 56, Heatmap, Peak pressure is highest in the Toe region (0.56 at 0° slope, 0.41 at 30° slope). As the slope increases, toe pressure decreases slightly but remains dominant, indicating toes play a crucial role in maintaining stability on inclines. Heel pressure remains relatively stable across slope angles (ranging from 0.36 to 0.42). Metatarsal pressure remains moderate but shows a slight decrease as the slope increases (from 0.35 at 0° to 0.34 at 30°), likely due to weight shifting forward. Midfoot pressure is consistently the lowest across all slopes (from 0.25 at 0° to 0.15 at 30°).

4. DISCUSSION

The results indicate that Foot zones show significant variations ($F = 61.56$, $p < 0.0001$, $\eta^2 = 0.0940$), with increased pressure in the toes and metatarsals at steeper inclines, confirming that forward weight shifts reduce heel contact (Ho et al. 2010; Chow & Lee, 2024). While slope angle has a moderate effect ($F = 4.11$, $p = 0.0428$, $\eta^2 = 0.0042$), posture remains the dominant factor influencing plantar loading. Interaction effects show that walking and kneeling increase pressure in the toes and metatarsals, while standing distributes pressure more evenly ($F = 24.18$, $p < 0.0001$, $\eta^2 = 0.1108$). As incline increases, pressure shifts from the midfoot to the forefoot, potentially increasing discomfort or injury risk ($F = 5.18$, $p = 0.0004$, $\eta^2 = 0.0156$). These findings align with Sen et al. (2020), but our results highlight a distinct redistribution at steeper slopes (30°), where toe and metatarsal pressures peak while heel pressure declines. In stooping, toe pressure remains consistently high, midfoot pressure declines with increasing slope, and heel pressure stays moderate with minor variations, indicating greater metatarsal stability across slopes. As the slope angle increases, novice workers intuitively adjust their weight distribution to enhance stability, which aligns with the findings of Choi et al. (2015).

On flat surfaces, the hindfoot exerts the highest pressure, but at 15° incline, heel pressure decreases by 27% (Ho et al., 2010), reinforcing the shift toward forefoot reliance on slopes. Further, the results show that standing consistently shows the lowest peak pressure across all slope angles. Kneeling and Stooping exhibit higher peak pressures, with an increasing trend as the slope angle rises. As the slope angle increases to 15° and 30°, kneeling and stooping show a rise in peak pressure, suggesting increased strain in these postures. The highest peak pressure is observed for kneeling at 30°, indicating greater foot loading at steeper inclines. The non-significant three-way interaction ($F = 1.11$, $p = 0.3451$, $\eta^2 = 0.0043$) suggests that posture, foot zone, and slope angle act independently, emphasizing the need to consider each factor separately in ergonomic footwear design and injury prevention strategies, stability. Simeonov et al. (2003) also found that increased slope angles reduce the effective base of support, limiting the body's center of gravity movement and increasing instability risks.

Among the evaluated machine learning models, RF demonstrated superior classification performance for plantar pressure data analysis, achieving training and test accuracies of 92% and 91%, respectively. This establishes RF as the most reliable model for detecting loss of balance events. Its ensemble learning approach enhances generalization and effectively handles non-linear relationships between key features such as slope angle, average pressure, and peak pressure. Additionally, RF's ability to operate efficiently in high-dimensional spaces makes it highly suitable for analyzing complex biomechanical data.

In comparison, the DT model exhibited moderate performance, with training and test accuracies of 85% and 82%, respectively. While DT provides high interpretability, it is more prone to overfitting and lacks the robustness of ensemble methods. SVM and KNN achieved comparable training accuracies of 89% and 88%, respectively, while their testing accuracies were 87% and 86%. These results indicate that while SVM and KNN are effective, they are slightly less reliable than RF for this dataset.

RF’s strength in identifying non-linear feature relationships further validates its use in plantar pressure classification. These findings align with Antwi-Afari et al. (2020), which highlighted RF’s effectiveness in construction activity recognition, and Izquierdo-Verdiguier & Zurita-Milla (2020), which emphasized its feature selection capabilities. Furthermore, Aria et al. (2021) reinforced RF’s predictive precision and flexibility in foot plantar pressure data analysis. Notably, RF has been widely adopted in acceleration-based action recognition, consistently outperforming other classifiers (Antwi-Afari, 2018).

Heatmap visualization (Figure 5) support RF’s capability to distinguish plantar pressure patterns across foot zones. The Toe region exhibited the highest peak pressure, which slightly decreased with increasing slope, indicating its critical role in stability. Heel pressure remained stable, while midfoot pressure was consistently the lowest across all inclines. These clear pressure distributions further confirm RF's ability to classify foot zones effectively, making it a highly efficient tool for automatic posture and pressure pattern classification in ergonomic analysis.

By using plantar pressure data from wearable insole systems, this study demonstrates the feasibility of detecting posture- and slope-related ergonomic risks among roofers. Through machine learning-based classification, suitable postures can be automatically identified and analyzed, offering safety managers a proactive tool to detect hazardous movements and reduce the risk of work-related musculoskeletal disorders (WMSDs). This study enhances the body of knowledge in construction safety by identifying critical foot zones and task-specific postures linked to biomechanical stress.

Limitations of the current study are a relatively small number of eight inexperienced participants, which can limit generalizability and reduce statistical power. A larger and more representative sample in natural environments with experienced roofers would enhance external validity and data quality. Furthermore, the controlled laboratory environment and focus on only three postures may not account for the range of real roofing environments, which typically include variations of postures and environmental factors. The authors want to have additional samples in the follow-up study, extending this analysis to other common roofing postures.

5. CONCLUSION

This study highlights the importance of plantar pressure distribution across various foot zones during kneeling, standing, and stooping on inclined surfaces at 0, 15, and 30 degrees. Posture exerts the most significant influence on peak plantar pressure, consistent with findings by Buldt et al. (2018).Foot zones also exhibit notable pressure variations, with toes and metatarsals experiencing increased pressure on steeper inclines, confirming a forward weight shift that reduces heel contact. While slope angle has a moderate effect, posture remains the dominant factor in plantar loading. As the incline increases, pressure shifts from the midfoot to the forefoot, potentially elevating discomfort and injury risks.

The findings indicate that different postures influence plantar pressure distribution uniquely, with kneeling increasing toe and metatarsal pressures while standing distributes pressure more evenly. In stooping, toe pressure remains consistently high, while midfoot pressure decreases significantly with increasing slope. Heel pressure remains moderate across all slopes, indicating that metatarsal stability is less affected by incline changes than other foot zones. The redistribution of plantar pressure at steeper slopes (30°) further highlights a shift toward forefoot reliance, reinforcing the importance of ergonomic footwear design and injury prevention strategies that account for posture, foot zones, and slope angles independently.

Machine learning, particularly Random Forest (RF), has proven to be the most effective classifier for analyzing complex plantar pressure patterns. Based on its high accuracy and efficiency, it is a comparatively more suitable classifier for its use in wearable sensor technology for real-time monitoring and for self-operating foot biomechanics classification. By integrating a blend of ergonomic solutions, best shoe solutions, and AI-driven risk assessment, foot pain is minimized, balance is improved, fall injuries are avoided, and the bottom line is a healthier and safer workforce—particularly for roofers who count on stability with each step they take.

6. FUTURE WORK

Future studies should incorporate subject variables like age, occupational exposure, BMI, sleep habits, overtime, and type of trade because they might influence the plantar pressure patterns and injury risk. Blending state-of-the-art biomechanical measurements like the center of pressure (CoP), surface electromyography (sEMG), and inertial measurement units (IMU) with natural environments and experienced roofers can enhance movement analysis and accuracy of data. Deep learning and neural networks may enhance classification accuracy above baseline models like Random Forest. Moreover, smart insoles and shoes created using new materials can enhance comfort, enable balance, and reduce musculoskeletal pain, thus enhancing workplace safety and production efficiency in high-strain jobs.

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