# A Deep Learning Approach to Real-Time Walking Surface Detection for Fall Prevention

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## Abstract

Falls are the leading cause of injury among older adults in the United States, causing 950,000 hospitalizations and 32,000 deaths in 2018 [1]. Automatically detecting walking surfaces can play a crucial role in fall prevention, enabling individuals to adjust their gait and safely navigate potentially hazardous terrain. For integration in wearable devices, the walking surface detection system must be accurate, efficient, and suitable for resource-constrained hardware.

To that end, we present a deep learning-based approach for walking surface detection, prioritizing classification accuracy while also considering real-time performance and deployment constraints. Our method introduces two core contributions. First, we present an effective strategy for sensor data augmentation and preprocessing. Second, we design an efficient convolutional neural network (CNN) architecture that achieves high accuracy with low computational overhead. Experimental results demonstrate that our approach reaches 91.5% accuracy in classifying five common walking surfaces using data from a single step.

## Walking Dataset and Preprocessing

This work uses the dataset established in [4]. To collect the dataset, an IMU sensor was deployed near the right ankle to collect accelerometer and gyroscope sensor readings while participants walked on five common walking surfaces in daily life, as shown in Fig. 1.


Figure 1. Sensor location and five walking surfaces [4].

To eliminate the impact of device orientation on classification results, we compose three-axis accelerometer readings at each timestamp into a scalar value as in equation (1), where $a_x$, $a_y$, $a_z$ represent accelerometer readings of x, y, and z axes, respectively. We similarly compose gyroscope readings.

$$a = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{1}$$

We use a method similar to [5] to extract data samples for training and testing our CNN model. We first normalize the composed acceleration time series using z-score scaling. We then detect acceleration peaks representing heel-strikes, restricting detected peaks to values at least two standard deviations above the sample mean, as shown in Fig. 2. We extract windows of 0.5 seconds (50 data points) centered around these peaks, each containing two-channel readings from one footstep.

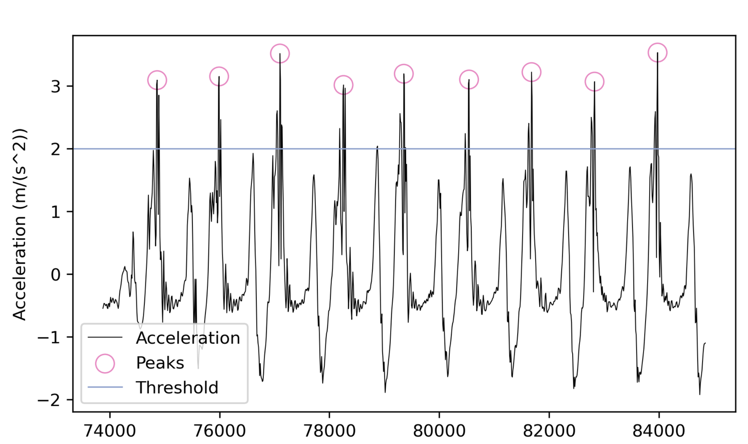


Figure 2. Detecting acceleration peaks from one walking sample.

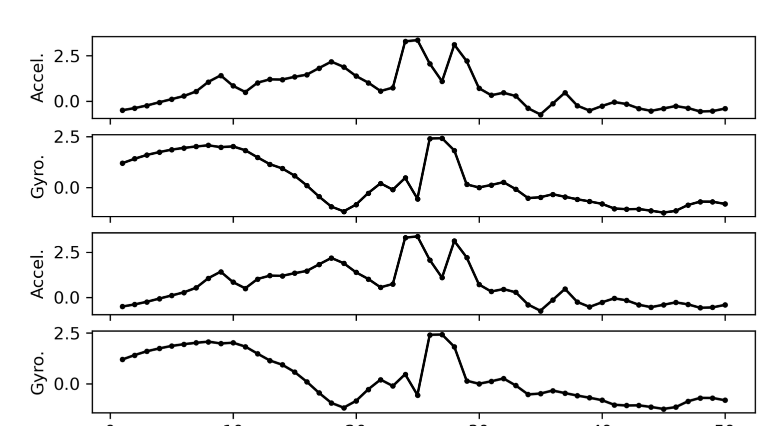


Figure 3. A 50x4 matrix after data augmentation.

We construct segments from normalized data, reducing variation between channels and segments and improving model performance. We also duplicate and stack each 50x2 sequence to obtain a 50x4 matrix (e.g. Fig. 3). Each matrix is paired with its corresponding walking surface label to form a classification sample; all such samples together constitute the dataset used for training and testing CNN models.

## CNN Architecture

Our goal is to design a new deep learning architecture that can achieve a strong balance between accuracy and computational efficiency for walking surface detection. As seen in Fig.4, our model has three convolutional blocks. Each convolution block contains a convolution layer, a batch normalization layer, and a leaky ReLU activation layer. Successive convolutional blocks have double the number of filters to increase model depth. In the final convolutional block, we include a maximum pooling layer to reduce the data sample dimension. Between each convolutional block, we add residual blocks with skip connections [2].

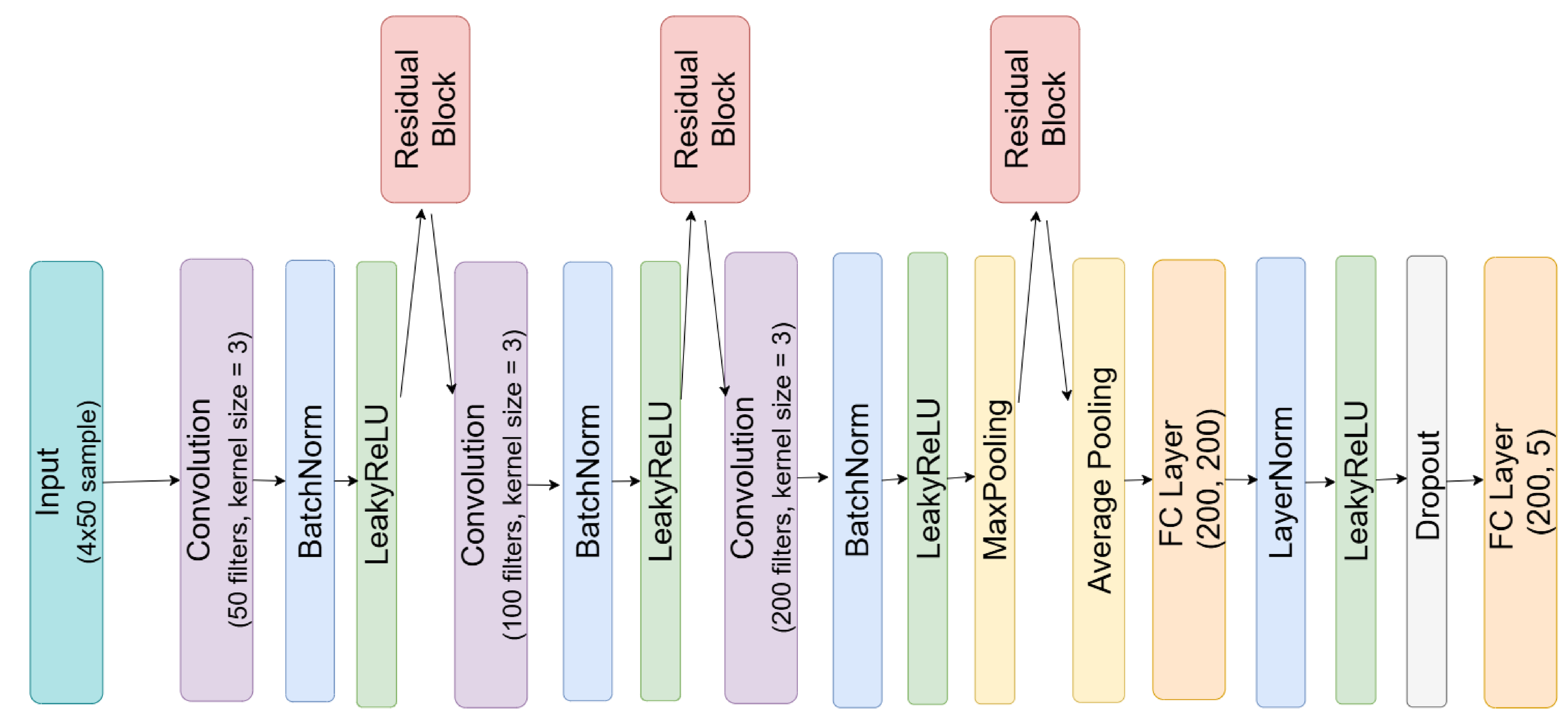


Figure 4. Proposed CNN architecture for walking surface classification

For each convolutional layer, we use 3x3 kernel dimensions to maintain a reasonable balance between computational cost and spatial feature extraction. We include batch normalization layers, leaky ReLU activation layers, and a dropout layer to improve model convergence and encourage intrinsic learning.

Additionally, we incorporate distributed residual blocks in our CNN architecture to help maintain gradient flow during backpropagation and allow deeper portions of our model to remember low-level features of the training data. Each residual block follows the structure described in the original residual learning paper [2].

## Experimental Results: Data Augmentations

Fig. 5 displays the impact of several data augmentation approaches on our model's classification accuracy. Normalization greatly improves our model's accuracy for 50x2, 50x4, and 50x6 segments. Although stacking reduces accuracy when using raw data, our proposed strategy of stacking to 50x4 with normalized data achieves the highest accuracy, improving performance by about 7.5% over results with raw 50x2 segments.

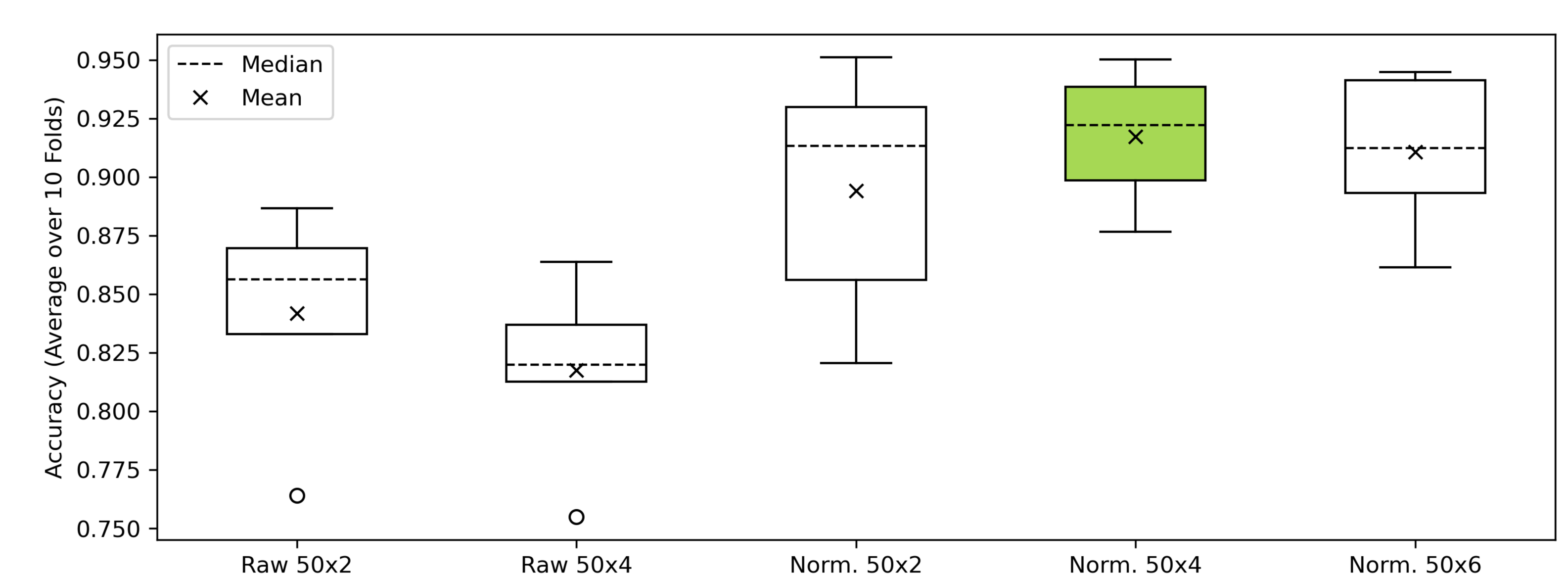


Figure 5. Our model accuracy with five different data augmentation approaches. The plots show the variation in accuracy between users, and our suggested strategy is shaded green.

## Experimental Results: Model Performance

The following results were obtained using 50x4 normalized data samples. Fig. 6(a) shows the comparison of Personalized Model accuracy for our model and traditional machine learning classifiers [4]. Our model improves surface classification accuracy by 10% compared to MLP, the highest performing machine learning classifier.

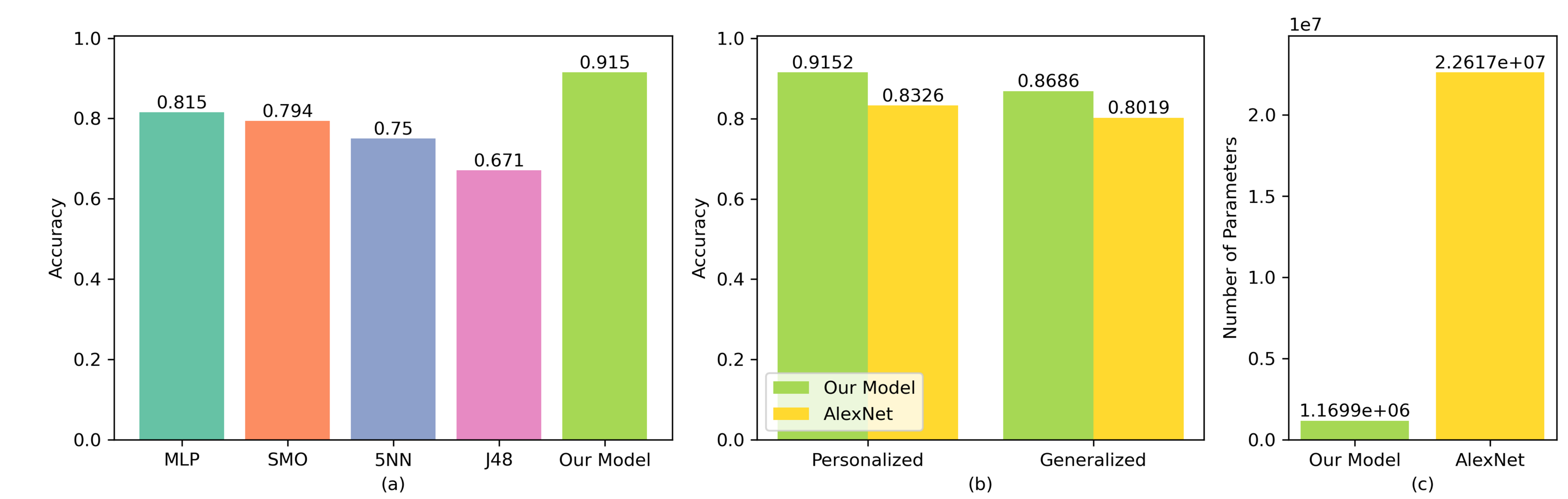


Figure 6. Performance comparison between traditional machine learning classifiers and existing CNN [4]

Fig. 6(b) shows the comparison of Personalized and Generalized Model accuracy for our model and AlexNet [3]. Our model outperforms AlexNet by 8.26% and 6.67% for the Personalized Model and Generalized Model, respectively. We were also able to decrease the number of trainable parameters in our CNN architecture by a factor of 19 compared to AlexNet, as shown in Figure 6(c). By incorporating residual blocks to create a deeper architecture, using the leaky ReLU activation function, reducing the size of the fully-connected layers to reduce the number of learnable parameters, and utilizing a dropout layer to avoid overfitting, we were able to design a model architecture specifically catered to our surface classification application.

## Conclusion and Future Work

Our novel CNN architecture coupled with our proposed data preprocessing techniques is more efficient than existing CNN architectures and provides high performance surface classification. By introducing sample normalization and channel stacking for 2D convolutions, selecting appropriate parameters, incorporating residual blocks for skip connections, and using the LeakyReLU activation function in our model design, we achieve a 91.5% accuracy for distinguishing five common walking surfaces in daily life, using data from a single footstep.

We plan to collect a more comprehensive dataset to account for varying walking characteristics in model training (different shoe types, pace, etc.). Currently, we have not measured our model accuracy when it is tested on a user who is not included in the training dataset. We will extend our work to utilize transfer learning for cross-domain adaptation analysis. Finally, we will develop a deep learning model to classify surface type from irregular walking patterns with a Long-Short Term Memory (LSTM) architecture.

## Acknowledgment

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## References

[1] Elizabeth Extrom et al. *Coordinated Care Plan to Prevent Older Adult Falls*. National Center for Injury Prevention, Control, Centers for Disease Control, and Prevention. 2021.

[2] Kaiming He et al. "Deep Residual Learning for Image Recognition". In: *CoRR* abs/1512.03385 (2015). arXiv: 1512.03385.

[3] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. "ImageNet Classification with Deep Convolutional Neural Networks". In: *Advances in Neural Information Processing Systems*. Ed. by F. Pereira et al. Vol. 25. Curran Associates, Inc., 2012. URL: https://proceedings.neurips.cc/paper_files/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf.

[4] Shuangquan Wang and Gang Zhou. "Poster: Foot-Floor Friction Based Walking Surface Detection for Fall Prevention Using Wearable Motion Sensors". In: *2023 IEEE/ACM Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE)*. 2023, pp. 179–180. DOI: 10.1145/3580252.3589414.

[5] Mariamawit Yohannes and Shuangquan Wang. *"Low-Delay and High-Accuracy Walking Surface Classification Through Heel Strike Detection"*. Salisbury University Summer Research Showcase. 2024.

Salisbury University 2025 * equal contribution ofann27@amherst.edu mmpuro26@colby.edu https://github.com/oliv-iam/surface-detection https://github.com/MayaPurohit/DeepLearningFallPrevention