SurfSole: Demonstrating Real-Time Surface Identification via Capacitive Sensing with Neural Networks

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Abstract. In this paper we present SurfSole, an untethered mobile system combining a smart sole prototype and mobile app to achieve real-time surface identification. We solely rely on the technology of capacitive sensing while choosing a neural network approach for classification. We evaluated different machine learning models with different layer architectures of 3-4 layers with 32, 64, 128, and 256 filters. The theoretical overall accuracy reaches from 74.85% up to 87.11%. While we retrieve data with 40Hz with a single window of 120 data points, we have a real-time detection delay of 3s.

Keywords: Artificial Intelligence · Surface Detection · Neural Networks · CNN · Capacitive Sensing · Real-Time · Smart Insole.

1 Introduction

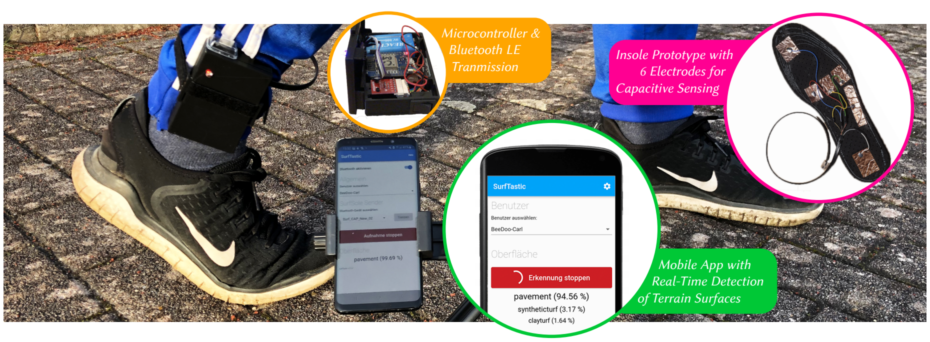


Fig. 1. Demonstrating SurfSole: The insole prototype, consisting of 6 copper electrodes, and a small box of electronics is worn on the right foot, while our mobile app "SurfTastic", running on an Android Smartphone detects the current terrain surface one is walking or running on.

Technological advancements are continuously transforming our daily lives, with wearable technology emerging as a crucial area of innovation. Current wearable technologies, such as smart insoles, also but slowly emerge. Currently, the primarily function of smart insoles is measuring pressure distribution for gait analysis, including a multitude of sensors, such as force-sensitive resistors [15], capacitive sensors [14], piezos [6], and other [7]. While these insoles are often in the stage of prototypes, they usually lack the capability to accurately identify the user's context, such as understanding the different surface types one is walking on. This may be a crucial information, while it can infer on the dynamic outdoor environment and the runner's energy expenditure. While there is a variety of sensors deployed with insoles, capacitive / electric field sensors [11], known for their sensitivity and versatility, offer a potential solution for this challenge by detecting subtle changes in capacitance caused by different surfaces.

Modern capacitive pressure sensors often utilize materials like polydimethylsiloxane (PDMS) and thermoplastic polyurethane (TPU) as dielectric layers [19]. These materials provide the necessary flexibility and durability for wearable applications [24]. Advanced insoles incorporate arrays of capacitive sensors to capture detailed pressure distribution across the foot, allowing for high-resolution mapping of plantar pressure [22, 17]. This is crucial for applications in gait analysis and posture correction [17, 18]. Capacitive sensors are often integrated together with accelerometers and gyroscopes to provide comprehensive data on gait and movement, enhancing measurement accuracy and reliability [16]. Real-time feedback on plantar pressure is important for the wearer as it can invoke a direct behavior change, such as helping to correct posture and improving balance, benefiting athletes and individuals undergoing rehabilitation [20]. The most related works are "PneuShoe" [7] and "CapSoles" [14], mobile shoe/insole-based systems that enable surface detection using conventional machine learning and enabling the distinction between sand, lawn, paving stone, carpet, linoleum, and tartan.

This paper presents SurfSole, a prototype system that consists of a redesigned insole capable of collecting capacitive data from various surfaces during walking or running. The collected data is processed using a Convolutional Neural Network (CNN) to classify the terrain type in real-time. The key contributions of this work include:

- Development of a slim and lightweight insole integrated with capacitive sensors and a compact controller for seamless data collection,
- Implementation of a data collection protocol using a mobile application,
- Design of a CNN model capable of distinguishing between multiple surface types with high accuracy,
- and the integration of the model into a mobile application, providing real-time feedback on the terrain type one is walking and running on.

2 Implementation

The prototype consists of several hardware components, including the insole, controller & PCB, and housing & more. Moreover, a software was developed, which consisted of several distributed parts, running on the microcontroller, server, and on an android app.

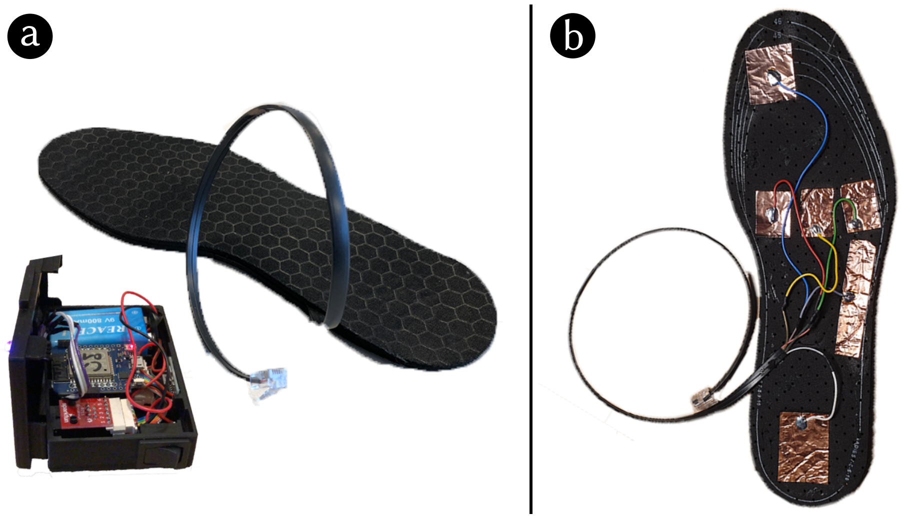


Fig. 2. a) Prototype with opened case, b) Opened insole displaying the copper electrodes.

2.1 Insole

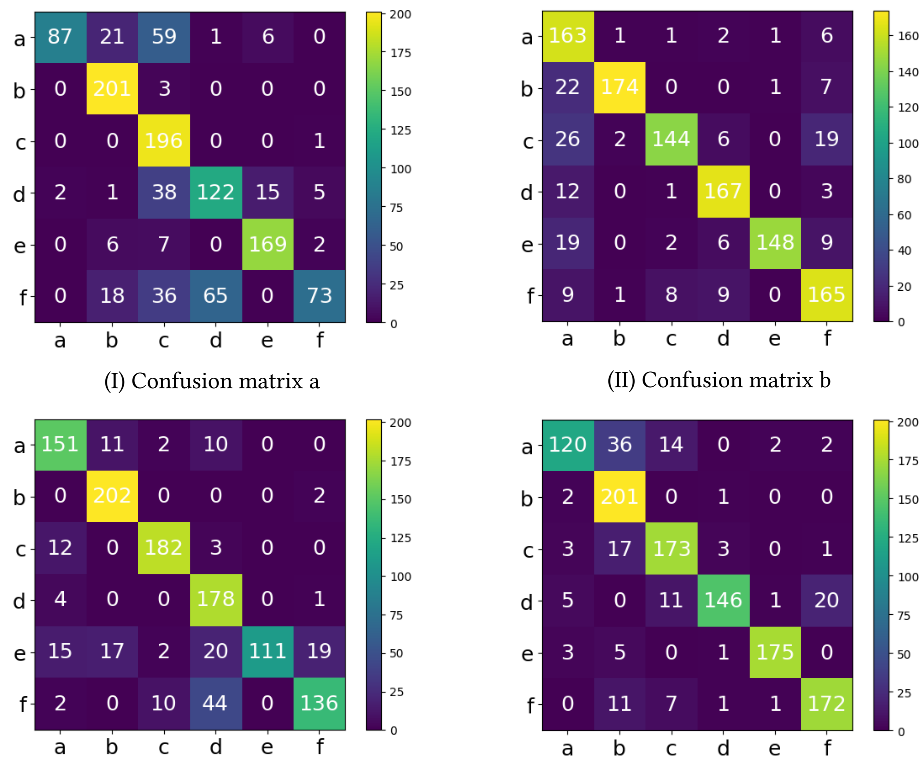
We evaluated several materials for the insole as a basis. The soft insoles from Budni drugstore [4] satisfied our needs. We implemented a total of six copper patches to the bottom side of the insole with double-sided tape. The copper patches [3] are originally used for snail protection in gardening but do just fine as capacitive sensing. Six electrodes resulted in 6 wires, which we integrated into a 6-pin cable with an RJ12 connector, which is an easy attachment to the case.

2.2 Controller & Circuit Board

Our printed circuit board (PCB) was designed to accommodate the pin layout from the ESP32 microcontroller board. The ESP32 conveniently incorporates a Bluetooth LE module, enabling a connection to the smartphone. Since the prototyping breakout board, which matches the development board, has interconnected sides, the circuit had to be designed extremely carefully, using isolated bridges for some connections to avoid short circuits. Our custom OCB utilizes both sides due to the unavailability of a single ground port. The placement of the PCB is in close proximity to the controller, to ensure relatively high integration density. The bulkiest part however, is the 9V battery.

2.3 Housing & More

The housing must accommodate a 9V LiPo battery. This 9V battery contains an internal regulator that provides a flat discharge curve against electrical jitters and noise, which would otherwise be present in measurements of analog signals, to ensure stable and reliable performance during the analysis. By using the compact shape of the battery and choosing a short development board for the controller, we were able to design a relativly slim case (approx. 4.5cm x 6.5cm x 2cm). The choice of a compact development board led to the ability to use a matching prototyping board that could sit directly under the controller, eliminating the loosely "integrated" circuits for sensing and a notification LED. The case has been designed using advanced 3D modeling projection techniques in Fusion 360 [1] by Autodesk. This design process involved multiple iterations.



(I) Confusion matrix a

(II) Confusion matrix b

(III) Confusion matrix c

(IV) Confusion matrix d

Fig. 3. Confusion matrices of different neural networks: (I) 3 layer CNN with 16, 32 & 64 filters, resulting in up to 74.85% accuracy; (II) 3 layer CNN with 32, 64 & 128 filters, resulting in up to 84.82% accuracy; (III) 4 layer CNN with 16, 32, 64 & 128 filters, resulting in up to 84.73% accuracy; (IV) 4 layer CNN with 32, 64, 128 & 256 filters, resulting in up to 87.11% accuracy. Classes: a) beach sand, b) clay turf, c) lawn, d) pavement, e) synthetic turf, and f) tartan.

3 Evaluation

3.1 Data Collection

As previous work already demonstrated some sort of study using conventional machine learning, we aimed to focus on emerging machine learning techniques, namely training a neural network model. Our objective was to obtain a minimum of 10 minutes of data per person, with each individual walking or running on each surface. To collect the required vast amount data for training a neural network, we utilized a mobile application developed with the Flutter framework [9]. This application facilitates communication with the controller software, enabling the initiation and termination of data recording through the continuous transmission of data via Bluetooth, a measure designed to conserve energy. The user interface of the application allows for the configuration of multiple data labeling parameters, including the username, surface type, surface condition (dry or wet), and shoe type. Upon completion of the recording, the app transmits the data to the SurfSole Data App, as illustrated in Figure 1. This web-based application enables real-time data verification, facilitating prompt detection and resolution of potential issues related to insole damage or Bluetooth connectivity disruptions.

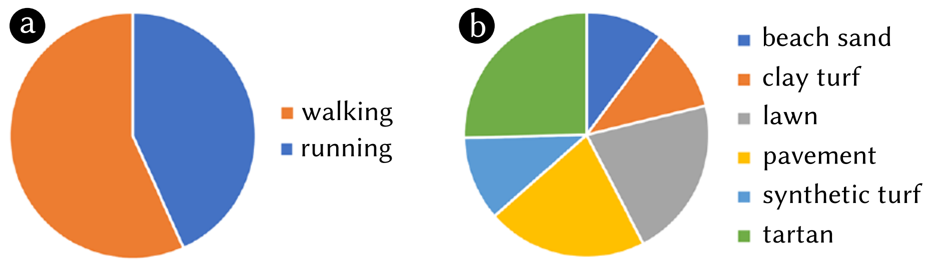


Fig. 4. Distribution of data collected: a) Distribution on walking style, b) Duration per surface type.

With two participants, we collected around an hour of training data in total. This is an adequate quantity of data to commence the ml model training phase. Figure 4 shows the distribution of our collected data in terms of walking speed, and surface type. Due to the lower energy exposure, walking speed is slightly more prevalent than running, as well as the surface types, which include pavement, tartan, and lawn, which are slightly more prevalent than, for example, beaches. Upon downloading the data from the SurfSole Data App, a zip file containing 982 CSV files has been generated for further data processing.

3.2 Model Training

Since we want to create some kind of real-time interaction, the network must be capable of performing classification on brief sequences. Additionally, the interrelation between two subsequent steps in a sequence may diminish with the passage of time. This is particularly evident when a step directly follows another, as the likelihood of them occurring on the same surface is high. In light of these considerations, a convolutional neural network (CNN) emerged as a promising initial approach, which is already indicated in literature [13]. We initially employed Keras, which precisely aligns with our objective, even though it requires the use of six channels [5].As Keras is basically an integrated part of Tensorflow [23] nowadays and Tensorflow has an option to convert a trained model to a smartphone friendly TensorFlow Lite [12] model, it was evident that the TensorFlow framework was the optimal choice for implementation. In accordance with recommendations, such as from Towards Data Science [21], we evaluated several iterations of the original network until we identified four candidate networks.

3.3 Results

The networks with 3 to 4 layers with 16 or 32 initial filters with doubling amount from layer to layer were trained on sequences as short as 40 to 120 datapoints (about 1-3 seconds walking or running) and came to acceptable results on an extracted testing data set as the confusion matrices in figure 3 clearly show. Eventually, our models converged after 71 epochs. Our results confirm that the detection of 6 diverse surfaces is feasible with a relatively modest CNN on brief sequences. However, as shown in figure 3, the accuracy remains highly variable across our four models; I) 74.85%, II) 84.82%, III) 84.73%, IV) 87.11%, indicating that the training process may require further optimization or additional data for training.

4 Real-Time Application

The exported TensorFlow Lite [12] model has been packaged into a mobile app, built with the dart-based [8] framework Flutter [9]. Further, we used the Flutter TFLite [10] package to distinguish the surface. In our app, we are able to select different models and adjusting some threshold settings to improve accuracy. The classification of the surface is triggered every 120 received data points. At a frequency of approximately 40 Hz, the detected surface in the SurfTastic app is updated roughly every three seconds if the confidence of the neural network's output is above 80% .

5 Discussion

5.1 Benefits & Key insights

Creating and putting SurfSole into action as a product would mean a major step forward in wearable tech and sports industry. For instance, identifying the terrain has a major impact when it comes to reduce running injuries and to optimize running performance.

The sleek case and compact development board improved the hardware design makes it comfortable for users and more reliable in comparison to most other prototypes demonstrated in literature. Using Bluetooth LE in combination with the SurfSole data collector app works perfectly with 40Hz data. Having the data directly on the phone enables for many more applications than just identifying terrain. The smartphones' power nowadays enable our app's for real-time data labeling makes it a reliable platform for prototyping.

The evaluation of different neural network architectures revealed that modest CNN could effectively classify surfaces based on brief data sequences. However, the accuracy varied significantly under different conditions, indicating the necessity for further optimization and extensive training data.

5.2 Challenges and Limitations

One of the major challenges encountered was the variability in the collected data. Different walking speeds, surface types, and environmental conditions (e.g., wet or frozen surfaces) significantly impacted the model's accuracy. This variability underscores the need for a more extensive and diverse dataset to train the neural networks adequately.

The current models demonstrated acceptable performance under controlled conditions but struggled under variable real-world conditions. Future work should focus on enhancing the robustness of the models through extensive data collection and pre-processing techniques such as normalization.

6 Conclusion & Future Work

In conclusion, the SurfSole project demonstrates a significant step forward in wearable technology and surface detection. By leveraging capacitive sensing in conjunction with neural networks, the prototype successfully identifies various terrains in real-time with an accuarcy of up to 87.11%. In our real-time implementation we can see that these results may be not always obtainable. In reality, we face many varying variables that impact accuracy. For instance, one day we might have slightly different weather conditions than other days (e.g., the surface is wet, slightly frozen, and therefore a harder surface). As we performed our tests in winter, we exactly faced these issues.

One of the most urgent next steps is to collect a significantly larger dataset for training the NN models, as the currently trained models still exhibit weak robustness. A broader dataset will result in adjusting the current network architecture and optimizing training parameters to improve for generalization. Currently, we deal with raw data. It is an open question whether pre-processing techniques such as regularization, normalization, etc. can help to significantly improve the model. Bagnall et al. [2] suggests it might further enhance the models' robustness.

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