ShoeTect2.0: Real-time Activity Recognition using MobileNet CNN with Multisensory Smart Footwear

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Abstract. In this paper, we introduce a proof-of-concept multi-sensory footwear prototype with artificial intelligence to facilitate human activity recognition. We equipped a shoe with a force sensitive pressure sensor, an accelerometer, and a gyroscope in order to detect human activity. Such sensors allow the system to capture and analyze data about various physical movements, which are further processed in order to detect specific human activities. To achieve accurate activity recognition, we trained and compared several models, which are two types of convolutional neural networks (CNN) and a conventional support vector machine (SVM). The system's accuracy in identifying activities like standing, sitting, walking, running, and jumping was evaluated, and scored highest using a MobileNet CNN with 83.33% accuracy. With this work, we demonstrate that a somewhat robust real-time activity recognition is feasible with prototypical hardware.

Keywords: Artificial Intelligence · Gait Detection · Neural Networks · CNN · Smart Insole.

1 Introduction

Wearable technology is revolutionizing our daily lives, with smart insoles emerging as a notable innovation. The most smart insoles are mainly designed for gait analysis with the help of a variety of sensor types.

Advanced sensing technologies that provide a number of enhanced sensing capabilities have been investigated and implemented. For example, force-sensitive [8] resistors provide accurate measurements of force or pressure through changes in resistance. Capacitive sensors [7] operate due to changes in capacitance, which can be highly sensitive to changes. Oppositely, piezoelectric sensors [3] generate an electrical charge under mechanical stress and hence are particularly applicable for insole measurements. Additionally, other innovative technologies [4] continue to push the boundaries of sensor capabilities, integrating new materials and approaches to improve performance.

Recent advancements in smart insole technology have significantly enhanced the capabilities of gait analysis systems. Modern smart insoles have taken advantage of the integration of multiple sensor types, which has substantially improved the accuracy

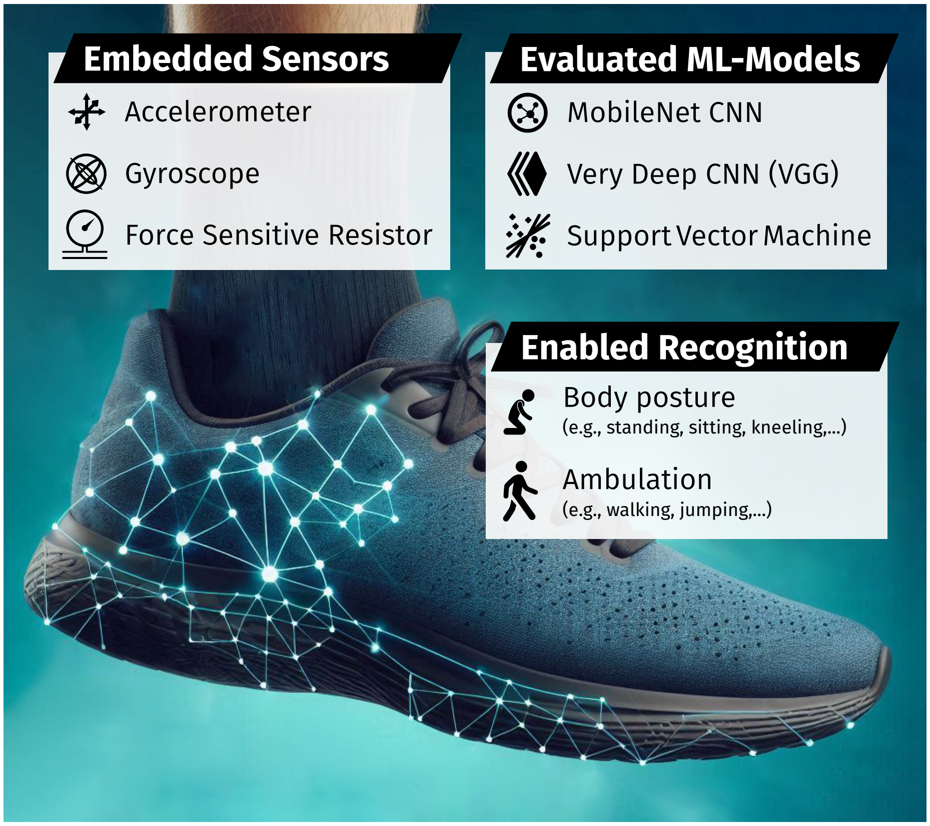

Fig. 1. Our prototype system features three sensors: Accelerometer, Gyroscope, and three FSRs. We then trained and compared three machine learning models, being a MobileNet CNN, VGG, and an SVM. We trained several models to detect body postures and ambulation activities in real-time.

and reliability of gait assessments. For example, Choi et al. [2] highlight the advantages of combining various sensor technologies within smart insoles, offering a more comprehensive evaluation of gait patterns.

In parallel, the application of machine learning models has further advanced gait recognition capabilities. Shen et al. [10] provide an overview of how deep learning techniques are applied to analyze gait data from insole sensors, showcasing the potential of these advanced models to effectively interpret complex gait patterns.

In addition, recent research has highlighted the importance of personalized approaches to gait analysis. Several studies [15, 14] have focused on how neural networks can be used to recognize people based on their individual gait patterns.

Building on these advancements, our work introduces a proof-of-concept multisensory method to unlock the rich data that our feet can provide. We equipped a shoe with a force sensitive resistor pressure sensor, a three-axis accelerometer, and a three-axis gyroscope. We employ a conventional machine learning approach, namely a SVM as well as two implementations of a convolutional neural network (CNN) for a typical data classification task.

The key contributions of this work include:

- Application of MobileNetV3 CNN for classifying activities, achieving approximately 83.33% accuracy in recognizing six postures and three movements activities.
- Implementation of a system capable of real-time activity recognition

2 System Design and Implementation

2.1 Hardware Setup

The smart shoe prototype was developed using an Arduino development board, which serves as the central processing unit for collecting and processing data from multiple sensors. The primary sensors integrated into the shoe include a three-axis accelerometer (MPU6050) and a membrane pressure sensor. These sensors were strategically placed to capture comprehensive foot movement and pressure data, essential for distinguishing between different gait activities. The MPU6050 sensor, located on the exterior of the shoe, measures acceleration and gyroscopic data. The membrane pressure sensor, positioned within the insole, has three sensing points at the big toe, fifth metatarsal, and heel, providing localized pressure data. The prototype is based on former work [6] and adjusted for this work. The smart shoe protoyp is presented in figure 2.

2.2 Software

The software for the smart shoe system was developed using the Arduino Integrated Development Environment (IDE) [1], which facilitates the programming and uploading of code to the Arduino board. The Arduino IDE is compatible with various programming languages, including C and Java, which allows flexible and efficient code development.

To ensure real-time data visualization and logging, SecureCRT [12] software was used. SecureCRT provides a terminal emulation interface for capturing serial data output from the Arduino board, enabling the storage of activity data in log files for subsequent analysis.

2.3 Data Acquisition

Data collection for this study involved monitoring the activities of 11 participants (11 male subjects, age: 22 ±1 years ; height: 176 ± 5 cm; body mass: 80 ± 10 kg) wearing smart shoes equipped with sensors. Each participant had an average shoe size of 260 ± 5 mm. The participants performed a series of predefined body posture activities, including standing, sitting, kneeling, squatting, leaning, and cross-leg sitting. For each

Fig. 2. The hardware prototype: a Converse-type shoe with low-level integration. We use breadboard prototyping with an Arduino Nano that streams the data via USB to a portable computer. Different to the previous version of ShoeTect [6], we waived on using the data gathered by the microphone and humidity sensor, although the sensors are still plugged. We believe the data not to be very meaningful for our activities.

activity, participants were instructed to maintain the posture for approximately 25 seconds. The sensors in the smart shoes captured data on acceleration, angular velocity, and pressure distributions.

In total, 66 sets of gait data were collected, with 11 sets corresponding to each of the six body posture activities. Each of the 11 participants contributed one set of data for each activity, resulting in a total of 11 sets per activity.

2.4 Classification

The classification of gait patterns was performed using a CNN based on the MobileNetV3 architecture . MobileNetV3 is a lightweight and efficient model designed for mobile and embedded applications, offering a good balance between computational efficiency and classification accuracy. This architecture incorporates depthwise separable convolutions and an inverted residual structure with a linear bottleneck, which significantly reduces the model's size and computational requirements [5, 9].

Fig. 3. The six body posture activities. (a) Standing. (b) Sitting. (c) Leaning. (d) Squatting. (e) Kneeling. (f) Cross-leg Sitting.

3 Evaluation and Results

3.1 Body Posture Recognition

The evaluation of the body posture recognition model was conducted using a dataset that included six distinct body postures: cross-leg sitting, kneeling, leaning, sitting, squatting, and standing. The model was trained over 100 epochs, and its performance was assessed using various metrics, including precision, recall, and F1 score. The results are shown in table 1.

Table 1. Performance Metrics for different Body Postures

Class	Precision (%)	Recall (%)	F1 Score (%)
cross-leg_sitting	60.00	100.00	75.00
kneeling	100.00	100.00	100.00
leaning	75.00	100.00	85.71
sitting	100.00	66.67	80.00
squatting	100.00	66.67	80.00
standing	100.00	66.67	80.00

The model demonstrated high precision in identifying various postures, achieving perfect scores of 100% for kneeling, sitting, squatting, and standing. However, cross-leg sitting exhibited a lower precision rate of 60%. In terms of recall, kneeling was perfectly identified with a 100% recall rate, while other postures showed a recall rate of 66.67%, except for cross-leg sitting, which achieved a perfect recall rate of 100%. The F1 scores, reflecting a balance between precision and recall, ranged from 75% to 100% across different postures. Overall, the model's performance was robust, with a mean precision of 89.17%, a mean recall of 83.33%, and a mean F1 score of 83.45%, highlighting its effectiveness in accurately distinguishing between various body postures.

3.2 Ambulation Recognition

For ambulation activities, the system was tested on three primary movements: jumping, running, and walking. Similar to body posture recognition, the model's performance was evaluated over 100 training epochs. The results for the trained model are shown in figure 2.

Table 2. Performance Metrics for different gaits

Class	Precision (%)	Recall (%)	F1 Score (%)
jumping	80.00	66.67	72.73
running	100.00	83.30	90.91
walking	75.00	100.00	85.71

The performance evaluation of the model in recognizing ambulation activities demonstrates robust accuracy and effectiveness. Running achieved the highest precision at 100%, indicating flawless identification, followed by jumping with a precision of 80% and walking at 75%. In terms of recall, walking excelled with a perfect recall rate of 100%, while jumping had the lowest recall at 66.67%. Regarding the F1 score, which balances precision and recall, running led with an impressive 90.91%, whereas jumping had the lowest score at 72.73%. Overall, the model exhibited strong performance across all three ambulation activities, with a mean precision of 85%, a mean recall of 83.33%, and a mean F1 score of 83.12%. This underscores the system's capability to accurately classify and differentiate between various types of movement.

3.3 Comparison with other Classifiers

To benchmark the performance, the MobileNetV3 model was compared with other classifiers such as the VGG model [11] and Support Vector Machines (SVM) [13]. The results for all three classifiers is shown in table 3. The results indicated that MobileNetV3 outperformed the other classifiers in both body posture and ambulation recognition tasks, achieving higher accuracy rates.

Table 3. Performance Metrics of Different Models

Category	MobileNetV3 (%)	VGG (%)	SVM (%)
ambulation	83.33	72.22	77.78
body gesture	83.33	83.33	72.22

These results underscore the efficacy of the MobileNetV3 architecture in the context of foot data-based activity recognition, offering a promising solution for real-time posture and movement monitoring applications.

4 Discussion

4.1 Benefits & Key insights

The smart shoe prototype integrates multiple sensors, including a pressure sensor and an MPU6050 sensor, to capture comprehensive foot data. This combination provides a holistic view of foot dynamics in various postures, enhancing the accuracy of gait pattern recognition and mitigating the limitations of relying on a single type of data. The system employs real-time monitoring of gait activities using an Arduino development board, operating at an output frequency of 10Hz. This allows for immediate feedback on foot posture and movement, facilitating quick adjustments and improving data accuracy. The use of SecureCRT software for serial port control allows for efficient storage of foot activity data. This system ensures the chronological and immediate saving of data, which reduces the manual workload and enhances the integrity of the experimental data. The MobileNetV3 is noted for its efficiency and accuracy in extracting relevant features from the data, outperforming traditional machine learning models like VGG and SVM in this context. The study highlights MobileNetV3's suitability for real-time applications and its potential for widespread use in gait analysis systems

4.2 Challenges and Limitations

The smart shoe prototype used in the study was a custom-built solution rather than a commercially available product. This decision led to certain compromises in terms of appearance and sensor integration. The use of a single shoe size (260 mm) limited the participant pool and may not accurately represent broader population dynamics. The pressure sensors used in the prototype provided data from only three points on the sole (big toe, fifth metatarsal, and heel), which may not fully capture the complete force distribution across the foot, which could impact the accuracy of the detected gait pattern. The data transmission in the prototype was conducted via a wired USB connection, which, while secure, restricted the mobility of the users and the range of data collection. The data collection was conducted under controlled conditions with a uniform ground surface. Variations in ground conditions, which were not accounted for, could potentially influence the accuracy of the data collected. Furthermore, the study did not consider the possible asymmetries between the left and right feet, which could affect the accuracy of gait analysis if not addressed.

5 Conclusion & Future Work

The study developed a smart shoe prototype aimed at recognizing gait patterns through the integration of multiple sensors and the use of machine learning models. Key findings include the effectiveness of the MobileNetV3 model, which demonstrated superior accuracy in recognizing both body posture and ambulation activities compared to other classifiers like VGG and SVM. The smart shoe system, despite its limitations, successfully validated its hypotheses, achieving a high accuracy rate exceeding 80% for gait recognition tasks.This research highlights the potential of using lightweight neural networks and multi-sensor data fusion in wearable technology to provide accurate real-time monitoring and feedback. Such systems could play a crucial role in various applications, including health monitoring, rehabilitation, and athletic performance enhancement.

The future development of this smart shoe system will focus on addressing the current limitations and exploring new avenues for enhancement. A crucial next step involves developing a mobile application that enables real-time activity recognition and user feedback. This application will leverage the data collected from the sensors to provide users with immediate insights and recommendations, enhancing the system's utility in everyday settings and potentially aiding in health monitoring and athletic training. o increase the accuracy and usability of the smart shoe, future iterations will incorporate more advanced sensors capable of capturing finer details in pressure distribution and motion tracking. Efforts will also focus on miniaturizing these sensors and integrating them seamlessly into the shoe's design, which will help reduce user discomfort and make the device more practical for prolonged use. Replacing the current wired data transmission setup with wireless technologies is another key area for development. This change will significantly enhance the user's freedom of movement and allow for more natural data collection, particularly in dynamic environments. To validate the system's robustness and generalizability, extensive field testing in diverse environments and with a broader participant base will be necessary. This will involve assessing the system's performance on various surfaces and under different conditions, helping refine its adaptability and accuracy. Exploring cutting-edge machine learning techniques is crucial for enhancing the system's performance. This includes investigating advanced deep learning architectures, such as transfer learning, reinforcement learning, and ensemble methods, which can potentially improve classification accuracy and computational efficiency. Implementing these techniques will further optimize the system, making it more capable of handling diverse and complex data.

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