A Machine Learning Approach for Real-time Gait Analysis

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***Abstract*—Clinical gait analysis is a non-invasive method used to identify abnormalities in human walking patterns. Traditional approaches rely on expensive and complex systems such as force plates, EMG, and motion capture, limiting their use to specialized clinical settings. In this paper, we develop a method for gait analysis that continuously monitor gait through wearables using a stick-and-peel form factor called pasteables, and a machine learning framework to support analysis of sensory data from pasteables for detecting abnormalities. We propose a methodology for designing such a pasteable device that makes use of available gait dataset to identify various monitoring parameters while obviating upfront user studies for parameter exploration and tuning. We apply the method in the design of a pasteable for detecting gait abnormalities through plantar pressure monitoring.**

***Index Terms*—machine learning, gait analysis, wearables, internet-of things**

I. Introduction

Clinical gait analysis is a non-invasive, comprehensive assessment tool used to evaluate and understand how individuals walk (gait). It is crucial for the diagnosis of disorders or abnormalities in movement patterns, which are characteristic of conditions like cerebral palsy or muscular dystrophy. Beyond diagnosis itself, gait analysis is crucial for evaluating the effectiveness of a particular treatment and adjusting treatment plans to optimize outcomes, as well as designing and fitting custom orthotics and prosthetics to fit an individual's unique gait needs. Unfortunately, the state of the practice in gait analysis today involves combining data from multiple equipment to measure a variety of parameters including (1) force plates to measure the reaction forces involved in human movements; (2) Electromyography for recording the electrical activity from skeletal muscles; and (3) mocap markers placed at feet, ankles, legs, hips, etc. that are captured through imaging to reconstruct the gait as the body moves. In addition to being highly complex, this analysis can only be performed in sophisticated orthopedic labs and consequently, precluding the possibility of continuously monitoring gait during normal day-to-day activities.

In this paper, we propose a novel approach for gait analysis that enables convenient, at-home monitoring. Our approach is based on *pasteables* [1], an emerging paradigm of wearable design that can integrate diverse sensors into a stick-and-peel form factor that can be attached to human body or clothing. We show that when combined with effective machine learning (ML), it is feasible to create a pasteable solution for detecting gait abnormalities with high accuracy. A key challenge in the design of such a solution is the need to perform sophisticated and costly user studies to identify the effective sensory parameters. A key contribution of our paper is a novel methodology to reduce such studies through use of available gait data. We show the effectiveness of the results in the design of a pasteable solution that uses plantar pressure inputs.

The paper provides the following important contributions.

- We develop a novel gait analysis methodology that permits at-home gait monitoring without requiring expensive setups in orthopedic laboratories.
- We develop a workflow for ML-based analysis on available gait data to determine an effective wearable configuration without requiring up-front investment on expensive user studies.
- We identify ML models for gait abnormality prediction using plantar pressure sensors with high accuracy.
- We identify the most effective sensor placement strategy to ensure accurate data collection.

II. Related Work

Gait abnormalities are associated with a variety of musculoskeletal and neurological disorders. To monitor pathological gait patterns effectively, researchers utilize various kinematics and kinetics data like plantar pressure etc [2][3]. Wertsch *et al.* [4] used seven force-sensitive resistors (FSRs) to record plantar pressure distribution and differentiate between walking and shuffling [5]. Subsequent work showed how to identify the importance of long-term data collection in groups where there is high variability in walking patterns [6]. Aminian *et al.* [7] used miniature gyroscopes to measure stride length and cadence, validated against a conventional motion capture system. Mannini and Sabatini [8] applied machine learning techniques on accelerometer data to detect gait abnormalities. Slijepcevic *et al.* [9] presented a framework for classifying gait disorders using ground reaction forces and centre of pressure data. Deep learning approaches, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory Networks (LSTMs), have also been explored for end-to-end gait classification [10]. Using computer vision, kinematic parameters such as joint angles, velocities, and accelerations can be efficiently extracted. Elham *et al.* leveraged Kinect skeletal tracking sequences to

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(a) (b)

Fig. 1: Vision for Gait Analysis for Abnormality Detection vis-a-vis Current Practice. (a) Current practice involves use of force plates in orthopedic lab. (b) Proposed approach monitors gait at home using pasteables.

derive these gait features [11]. Their study evaluated two machine learning models—one instance-based discriminative classifier and one dynamic generative classifier—to differentiate between normal and pathological gait. Javier *et al.* proposed a vision-driven approach for diagnosing gait impairments. From a single video input, they extracted semantic and normalized gait features across eight walking styles—one typical and seven representing various impairments [12]. Zakaria *et al.* [13] conducted a study to differentiate the gait patterns of children with Autism Spectrum Disorder (ASD) from those of typically developing children. Chen *et al.* [14] introduced a streamlined approach for analyzing parkinsonian gait using monocular video footage. Their method employed kernel-based principal component analysis to quantify and classify gait characteristics efficiently. Chen *et al.* [15] also employed principal component analysis (PCA) combined with a support vector machine (SVM) to classify multiple gait styles, including toe-in, toe-out, excessive supination, heel-walking, and normal gait patterns. Adhikary *et al.* has shown that it is possible to use wearable sensors with accelerometers and gyroscopes to distinguish between healthy and abnormal gait patterns [16]. By applying machine learning on collected motion data, the system achieves over 90% accuracy and shows promise for remote gait monitoring using smart devices. These advanced models have shown improved accuracy in recognizing complex gait patterns. The idea of pasteables was introduced for applications like fitness and athletics [17]. It has also been used to monitor light pollution [18].

III. System Overview and Key Design Challenges

A. Gait Abnormality Detection: Current Practice vs. Proposed Wearable System

Fig. 1 provides a visual comparison between the current practice in gait analysis and our proposed methodology. Gait abnormality detection in clinical settings relies on pressure plates embedded into the ground. Individuals walk over these plates wearing motion capture markers on their body. Although this setup provides high accuracyi, it is constrained to lab environment due to its high cost, large and rigid infrastructure, and precise calibration requirements, making it less compatible for wearable integration. We instead propose a wearable device that will allow people to monitor gait pattern and detect abnormality at home. The idea is to use a special stick-and-peel device called *pasteable* [1] which can be easily attached to the underside of a foot or insoles of shoes like a bandaid. The pasteable collects relevant data on the user's gait which is transmitted to a local or cloud-based ML platform for automated abnormality detection. This will cause less frequent clinic visits, improve patient comfort, and enable gait analysis with data from the patient's natural environment.

B. Simulation-Driven Method for Wearable Design

The primary challenge in designing a wearable for continuous monitoring for gait analysis is to identify the appropriate sensors that are small, feasible for wearable integration, affordable, and capable of capturing gait-related signals with sufficient fidelity, especially when attached to less stable surfaces like shoes or insoles. This precludes many sensors currently used in clinical practice, *e.g.*, it is clearly infeasible to recreate through wearables the laboratory setups involving MoCap sensors and gait capture via multiple cameras and videos. Conventionally, identification of appropriate sensors in a wearable is achieved through a series of user studies after building a prototype. Such work requires a feedback loop involving prototype design, user studies, effectiveness evaluation and refinement. This process is slow, expensive, and resource-intensive, involving multiple user studies specifically in the exploration phase.

A primary contribution of our methodology is to eliminate this exploration loop. Fig. 2 summarizes the overall workflow followed in developing our system, which is explained in detail in Section IV. Our approach makes use of available datasets to identify and tune machine learning models. Obviously, such datasets do not use continuous monitoring. A key aspect of our contribution is a methodology to "massage" these datasets such that ML analysis on such data can be effective for real-life scenarios, *e.g.*, we integrate methodology to mimic sensor inaccuracy in wearables through introduction of noise in the data that corresponds to the accuracy of the targeted sensors, and we mimic the impact of introducing pasteable on shoe insoles (vis-a-vis on the underside of the foot) by reducing the amount of sensory data available to reflect the scenario where the shoe is taken off for certain periods of time in a day. Note that this two-step approach, using an ML model to assess viability followed by real-world validation through wearable deployment, has been effectively applied in related areas of clinical diagnostics, such as infectious disease detection [19].

IV. Identifying and Tuning Machine Learning Models

Design of a wearable solution requires identifying viability of sensory and ML parameters effective for gait analysis. In this section, we show how to achieve that without first committing to costly hardware development. Our methodology

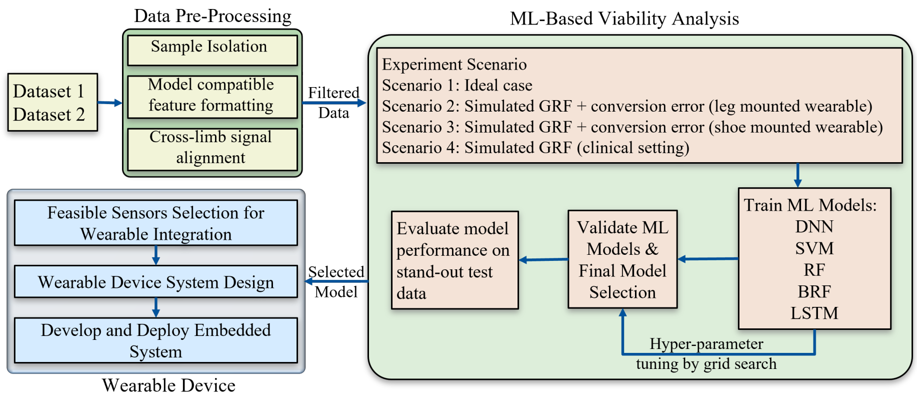


Fig. 2: Workflow for Gait Disorder Detection System

uses publicly available ground reaction force (GRF) datasets to simulate various levels of sensor data inaccuracy in real-world scenario. The goal is to determine whether our model can accurately detect gait abnormality on these simulated signals. By establishing design decisions based on strong machine learning performance, this analysis helps reduce development risk and avoids unnecessary hardware iterations.

A. *Viability Analysis Framework*

The viability analysis consists of two main steps: (1) pre-processing and structuring the GRF data for both temporal (sequence-based) and non-temporal (flattened) models, while ensuring alignment between left and right leg signals and maintaining clean train-test splits to avoid data leakage; and (2) training and evaluating multiple machine learning models, such as Long short-Term Memory Networks (LSTM), Deep Neural Networks (DNN), Support Vector Machine (SVM), Random Forest, and Balanced Random Forest, across various experimental setups. These experiments simulate real-world deployment scenarios such as environmental noise and different sensor placements (foot, shoe, etc.), allowing us to assess model robustness under practical constraints. Hyperparameter tuning, cross-validation, and individual component-wise analysis (*e.g.*, vertical, anterior-posterior, mediolateral forces) are employed to further optimize and validate each model's performance.

B. *Dataset Description*

We use two publicly available datasets, the GaitRec dataset and the Gutenberg Gait Database. Together, these datasets provide a comprehensive collection of ground reaction force (GRF) recordings from both healthy individuals and patients with gait disorders.

- Dataset 1 (GaitRec): This dataset contains GRF data from 2084 patients with musculoskeletal impairments and 211 healthy controls, recorded across thousands of walking trials [20].
- Dataset 2 (Gutenberg): This dataset contains data from 350 healthy individuals, collected under consistent lab conditions [21].

We use GaitRec dataset as the primary dataset for the majority of our experiments, given its large sample size. However, the dataset is highly imbalanced, with significantly more abnormal than healthy samples (abnormal-to-healthy ratio approximately 1:10). To evaluate whether balancing the class distribution will have impact on model performance, we later integrate the Gutenberg dataset with GaitRec. This results in a combined dataset containing 2645 unique subjects and over 84,000 gait trials, which we use to evaluate generalizability and model robustness under more balanced conditions.

TABLE I: Summary of Simulation-Based Data Setup

Simulation Scenario	**Noise**	**Conversion Error**	**Training Samples**
Ideal	✘	✘	Full
Wearable on Foot	✔	✔	Full
Wearable on Shoe	✔	✔	1/3
Clinical	✘	✘	Sparse

C. *Experiment Design Under Simulated Real-World Conditions*

In order to evaluate robustness of machine learning models in gait abnormality detection, we have developed an experimental framework that simulates different real world data scenarios, from laboratory settings to everyday at-home use. Different data scenarios that are considered in our framework are described as follows:

a) Ideal Scenario – Clean Reference Dataset: In this ideal data scenario, we assume high-quality GRF data is collected using force plates. This dataset is free from noise, signal distortion, and sampling artifact. This setup represents the best-case scenario for model performance.

b) Home setting Foot-Mounted Wearable Scenario: The foot-mounted wearable scenario simulates data collection using pasteables attached to the foot at home. To reflect real-

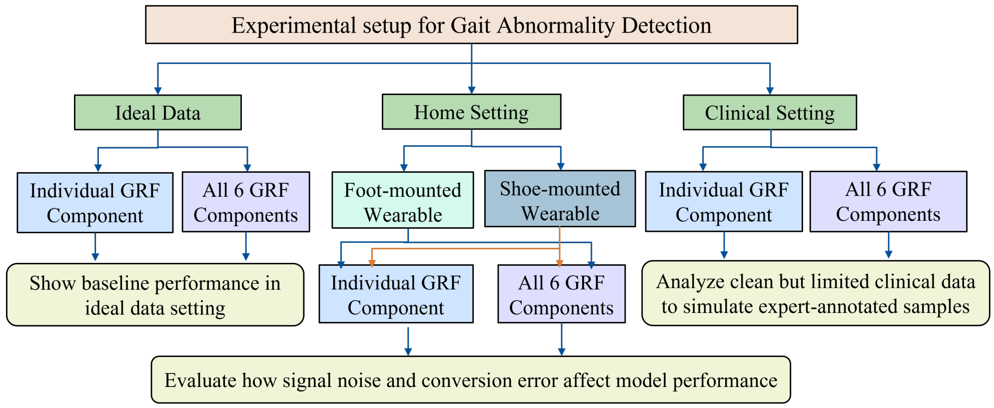


Fig. 3: Summary of Experiment Setups

world variability during sensor-based data collection, Gaussian noise is introduced into the signals to account for environmental and hardware-induced fluctuations. Additionally, systematic conversion errors are also introduced to simulate inaccuracies that may arise when translating plantar pressure data into full GRF vectors. While force plates offer precise GRF readings, their bulk and calibration needs make them impractical for continuous, at-home monitoring. Pasteables, though more feasible for daily use, only capture partial information. Research shows that machine learning techniques can estimate GRF components from pressure data with reasonable accuracy, but inherent estimation errors persist [22]. Incorporating these imperfections provides a more realistic evaluation of model robustness outside controlled settings.

c) Home setting Shoe-Mounted Wearable Scenario: Building on previous setting, the shoe-mounted wearable scenario simulates pasteables placed inside a shoe. In addition to the noise and conversion error from the previous scenario, this setup introduces data sparsity by reducing the number of training samples. This reflects real-world challenges such as inconsistent device usage, where users may not always wear the sensor-equipped footwear. The goal is to assess how models perform under both real world conditions.

d) Clinical Setting Scenario: In this scenario, we assume GRF data is collected under clinical supervision using precision-grade equipment. While data quality remains strong, the number of trials per subject is limited, reflecting typical constraints of clinical data collection. This condition evaluates how models handle scenarios with clean but scarce data, a common situation in medical studies.

Each scenario examines the effects of varying data quality (e.g., clean vs. noisy, measured vs. estimated GRF) and data quantity (e.g., complete vs. sparse datasets) on model performance. They also test model generalization across different populations and conditions. By simulating multiple realistic use cases, including the constraints of pasteables and the approximation of GRF from plantar pressure, this experimental design ensures a comprehensive and scientifically grounded assessment of model robustness. Such a framework is essential for validating machine learning solutions aimed at enabling continuous, at-home gait monitoring.

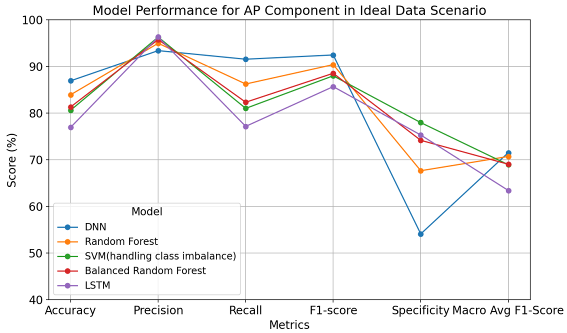
D. Data Preprocessing

We prepare the data for model training and create the experimental data setups mentioned in previous subsection by applying a series of preprocessing steps focused on ensuring proper model compatibility, and structural consistency.

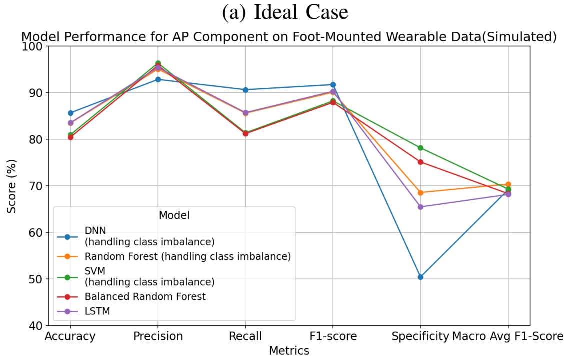
a) Sample Isolation: Since gait sessions were captured over extended periods and under varying walking conditions, we adopt a subject-session-wise isolation strategy for temporal models (e.g., LSTM) to preserve natural temporal variation critical for learning generalized sequential patterns across diverse conditions, while still maintaining a clear separation between training and test data to prevent leakage. For non-temporal models (e.g., DNN, SVM, Random Forest, Balanced Random Forest), we apply subject-wise isolation, ensuring that data from a given participant is entirely contained within either the training or the testing set, thereby preventing data leakage across all model types.

b) Model-Compatible Feature Formatting: We prepare the dataset to support both temporal models (e.g., LSTM) and non-temporal models (e.g., DNN, Random Forest, SVM). For temporal models, we maintain the original 101 time-step structure of each GRF cycle. For non-temporal models, we flatten the time series into fixed-length vectors and apply Principal Component Analysis (PCA) to reduce dimensionality while preserving essential variability.

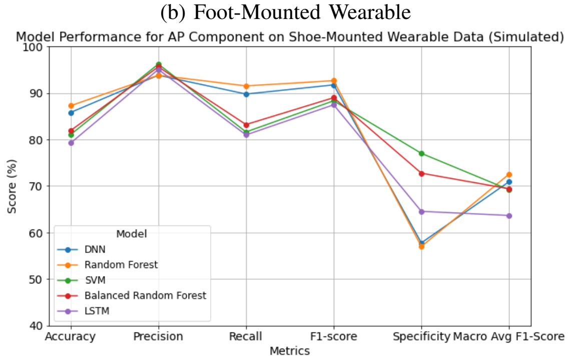
c) Cross-Limb GRF Alignment: For experiments involving signals from both legs or full 3D GRF inputs, we ensure signal alignment by matching corresponding features from the left and right legs of the same subject, session, and trial. Only trials with complete and synchronized left-right data across all GRF components (AP, ML, V) are retained, ensuring consistency in case of combined feature setups.



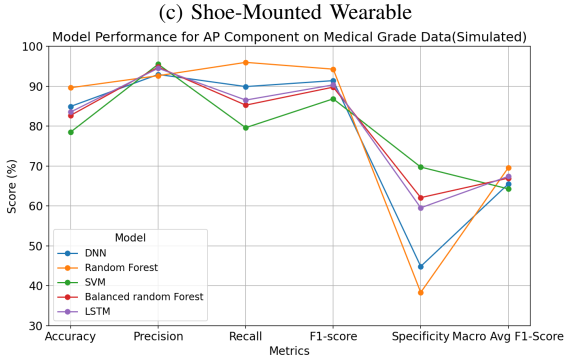
(a) Ideal Case



(b) Foot-Mounted Wearable



(c) Shoe-Mounted Wearable



(d) High Quality Clinical Setting

Fig. 4: Comparison of model performance on a single GRF component (Anterior-Posterior) across various experiment setups.

E. ML Model Development

We have developed and evaluated both temporal and non-temporal machine learning models to classify gait patterns as either normal or abnormal. Our evaluation process is organized to systematically compare model performance across different data quality, and input configuration scenarios.

a) Model Selection:

- Temporal Models: We develop Long Short-Term Memory (LSTM) networks to capture time-dependent variations throughout the gait cycle. Our LSTM model is designed to learn temporal patterns across 101 time steps per trial. To enhance performance, we utilize bidirectional LSTM variants.
- Non-Temporal Models: We also develop non-temporal models, like conventional classifiers such as Support Vector Machines (SVM), for finding optimal decision boundaries and conventional feedforward networks like Deep Neural Networks (DNNs). We also implement ensemble methods like Random Forest, Balanced Random Forests using flattened, PCA-transformed feature vectors to remove temporal dependencies.

b) Training and Hyperparameter Tuning: We use grid search to tune key hyperparameters such as learning rate, batch size, regularization strength, number of layers and apply k-fold cross-validation to prevent overfitting. For the temporal model (LSTM), we use 256 memory units, a sigmoid activation function in the output layer, and binary cross-entropy as the loss function. For the deep neural networks (DNNs), we identify the optimal configuration: a learning rate of 0.001, batch size of 64, regularization strength (alpha) of 0.0001, and hidden layers (768, 512, and 256), optimizer $= 'adam'$. For random forests (RFs) the key parameters are tuned as $n\_estimators = 100$, $max\_depth = 10$, $min\_samples\_split = 5$, and $min\_samples\_leaf = 2$, $class\_weight = balanced$ to handle class imbalance. We use similar configurations for balanced Random forests (BRFs). For support vector machines (SVM) we use kernel = 'rbf' to capture non-linear relationships in the data, $C = 1.0$ to balance the trade-off between maximizing the margin and minimizing classification error, and $class\_weight = balanced$ to address class imbalance during training.

F. Performance Evaluation

Models are evaluated on held-out test data using standard classification metrics: accuracy, precision, recall, specificity and F1-score. During analysis we use PCA to reduce the feature dimensionality. But we observe that the principal components reflect the majority (abnormality) class more decreasing the minority class (Healthy Controls) representation. It is further observed that it affected DNN more than RF and SVM. In order to solve the class imbalance problem in GaitRec dataset, especially for DNN model, we implement a combined sampling strategy: first we use SMOTE to perform oversampling and then perform undersampling using RandomUnderSampler.This combined sampling strategy

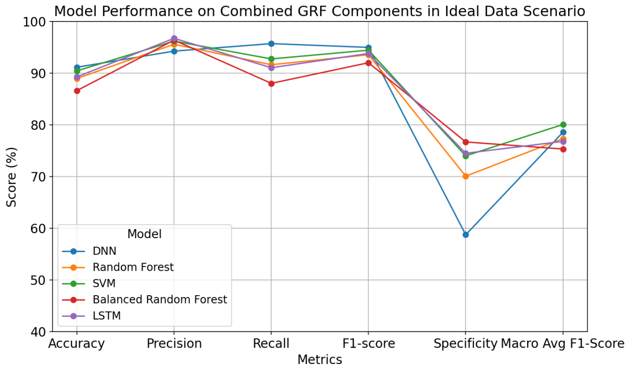


Fig. 5: Model Performance on Combined GRF Components (all 6) in Ideal Data Scenario

noticeably improve the overall performance of the model. We also compare performance across experimental scenarios to identify models that maintained high sensitivity under ideal, home and clinical settings.

a) Individual GRF Component Performance Across Experiments: To evaluate models' robustness under different real-world conditions, we compare their performance using a single GRF component (e.g., Anterior-Posterior) across all the experiment setups described in IV-C. Each subfigure in Fig. 4 shows model performance in terms of accuracy, precision, recall, F1-score, and specificity for all five models under each condition, highlighting how each model degrades or sustains performance across the different real world scenarios.

Among the five developed models, SVM consistently maintains reliable performance, particularly in terms of specificity. SVM has the highest specificity across all experimental setups (never falling below 70%) while achieving competitive scores in other metrics. This makes SVM effective at detecting the minority (healthy) class, which is critical since there is a severe class imbalance in the dataset (2084 abnormal vs. 211 healthy). DNN and RF demonstrate high accuracy and recall, but consistently show low specificity (often dropping below 50%) which means they have a tendency to overpredict the majority class, limiting their reliability. In contrast, Random Forest provides strong specificity for vertical GRF component.

Balanced RF and LSTM show consistent performance, with no extreme highs or lows. While they do not lead in any single metric, their stability in performance in all conditions make them dependable for applications where moderate, balanced performance is acceptable. LSTM has moderate specificity, improving when all components are considered together but generally trailing SVM and Balanced RF. SVM and Balanced Random Forest consistently achieve the highest specificity across scenarios, indicating superior performance in correctly identifying the minority class.

b) Combined GRF Components Performance in Ideal Data Scenario using Dataset 1: We have evaluated the performance of all five models on combined GRF components (AP, ML,V) under the ideal scenario (clean data) using Dataset 1.

TABLE II: SVM Performance Across Different Experimental Setups (on Dataset 1)

Metric	Ideal	Foot-Mounted	Shoe-Mounted	Clinical
Accuracy	90.44%	91.06%	90.19%	88.27%
Precision	96.20%	96.07%	96.19%	96.49%
Recall	92.76%	93.63%	92.47%	90.09%
F1-score	94.45%	94.83%	94.29%	93.18%
Specificity	74.00%	72.81%	74.00%	73.56%
Macro Avg F1	80.06%	80.82%	79.69%	75.59%

TABLE III: SVM Performance Across Different Experimental Setups (on Class Balanced Dataset)

Metric	Ideal	Foot-Mounted	Shoe-Mounted	Clinical
Accuracy	98.72%	98.98%	98.66%	98.11%
Precision	99.54%	99.71%	99.69%	99.18%
Recall	99.01%	99.14%	98.79%	98.72%
F1-score	99.28%	99.42%	99.24%	98.95%
Specificity	96.49%	97.76%	97.66%	92.61%
Macro Avg F1	96.91%	97.53%	96.79%	94.81%

Fig. 5 shows model-wise performance across all metrics where most models achieve high accuracy, precision, recall, and F1-score above 90%. However, specificity varies significantly across models: DNN and Random Forest exhibit sharp drops, suggesting a strong bias toward the majority (abnormal) class, while SVM achieves the highest specificity (around 80%) with balanced performance in other metrics. Balanced Random Forest achieves an accuracy of approximately 87% while LSTM shows a stable performance across all metrics, avoiding large fluctuations and offering reliable generalization.

Based on its ability to preserve specificity without compromising overall performance, we select SVM as the best performing model for this experiment. Table II shows SVM model's performance across different experiment setups, showing consistent performance with high accuracy, precision, and recall in all conditions. It maintains stable specificity (as low as 72%) despite class imbalance, making it a reliable and balanced classifier for both clinical and real-world scenarios.

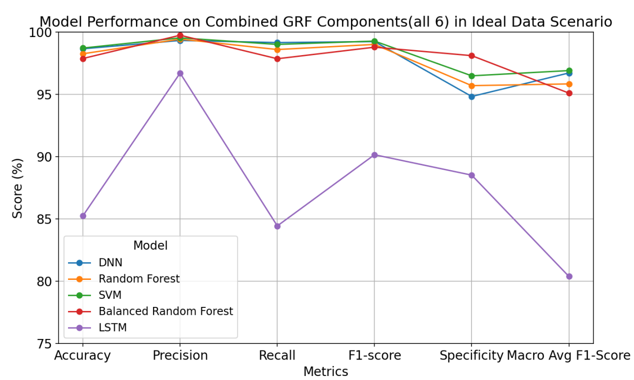


Fig. 6: Model Performance on Balanced GRF Components in Ideal Data Scenario

c) Performance Evaluation on Balanced Participant Data: We evaluate how class imbalance impacts model performance, by creating a balanced dataset by combining the GaitRec dataset with healthy participant data from the Gutenberg dataset. This combined dataset, hereafter referred to as the "*Balanced Dataset*" contains 2084 abnormal participants and a total of 561 healthy participants (211 from GaitRec and 350 from Gutenberg), improving the abnormal-to-healthy ratio.

Fig. 6 shows the performance of all five models on the balanced dataset under the ideal data scenario, combining all three GRF components (vertical, anterior-posterior,and medio-lateral). Compared to the models' performance on the original imbalanced data, we observe a noticeable improvement in specificity across most models, particularly for DNN and Random Forest, which previously showed sharp drops. At the same time, recall and accuracy remain stable or slightly improve, indicating that balancing participant representation enhances the model's ability to distinguish between healthy and abnormal gait patterns without compromising overall performance. Table III shows SVM model's performance across different experiment setups in the balanced dataset.

Summary of Performance Evaluation: LSTM performance remains consistent across experiments and is unaffected by class or sample distribution. Across all experiment scenarios, whether using individual or combined GRF components, under imbalanced and balanced data conditions, SVM and Balanced Random Forest (BRF) consistently emerge as the most reliable classifiers. Both models demonstrate stable and balanced performance, with SVM slightly outperforming BRF, particularly in terms of detecting the abnormal class while maintaining a competitive performance for detecting the healthy class. SVM's ability to preserve true negative detection while maintaining high recall and F1-score suggest that it is the most promising model for deployment in wearable-based gait assessment systems, offering strong generalization across a variety of realistic data scenarios.

V. Pasteable Design and Placement

Guided by our analysis, we developed a pasteable prototype to collect plantar pressure data. The device is made with flexible printed circuit (FPC) that conform to the contours of the user's foot, ensuring both comfort and consistent sensor contact which are crucial for accurate data acquisition.

A. Pasteable Devices and data Collection

The pasteable system comprises two core modules: a pressure sensor array and an embedded processing unit shown in Fig. 7(a) and the form factor of the pasteable prototype is shown in Fig. 7(b). The sensor array uses Teckscan's A301-100 resistive pressure sensors, chosen for their thin and flexible structure. Currently, ten sensors are placed in high-pressure areas identified from standard plantar pressure maps. The array supports scalability of up to 32 channels. The embedded hardware handles signal acquisition, processing, and power management. A multiplexer selects input channels, and the microcontroller samples analog signals using its built-in Analog-to-Digital Converter (ADC). Since gait-related signals are typically low-frequency (around 0 to 1 Hz), we designed a low-noise amplifier and generated the required voltage levels using a buck-boost converter and Low Dropout Regulator regulator (LDO), powered by a lithium-ion battery. The system includes interfaces and controls for data collection from the device. Data is transmitted via UDP protocol, packaged into structured packets for downstream processing. The system supports machine learning-based analysis for gait classification and anomaly detection. A web-based visualization dashboard enables monitoring plantar pressure in real time and receive alerts for abnormal gait patterns.

Under continuous sampling and data uploading at 100 Hz for 5 minutes with a 3.7 V power supply, the system showed a peak current of 110.04 mA and an average current of 90.95 mA, corresponding to a peak power of 407.11 mW and an average power of 336.49 mW. Commercial 3.7 V lithium batteries with PH2.0 mm connectors typically provide 300–2000 mAh capacity, supporting 3–20 hours of continuous operation, which is sufficient for daily home use.

B. Pasteable Placement

The reliability of gait analysis using machine learning depends on the location where the pasteable is placed. To find the optimal location for attaching pasteables, we divided the foot into eight regions: heel (R1), medial mid-foot (R2), lateral mid-foot (R3), medial forefoot (R4), central forefoot (R5), lateral forefoot (R6), hallux (R7), and toes (R8) as shown in Fig. 7(c). These regions follow widely accepted foot segmentation methods in gait studies [10]. Our prototype captures pressure data directly from the bare foot using soft, skin-friendly sensors. This direct placement helps avoid signal distortion that can come from wearing shoes and improves the accuracy of the pressure readings.

We train our models using several algorithms, including Convolutional Neural Networks (CNNs), Long Short-Term Memory Networks (LSTM), eXtreme Gradient Boosting (XGBoost), and Support Vector Machines (SVMs). To understand how much each foot region contributes to the model's accuracy, we use Shapley value analysis that shows the importance of each input based on its impact on predictions along with XGBoost [23]. This helps comprehend how each anatomical region affects model decisions. Based on our studies so far, we see that regions like the heel and forefoot carry more useful information for prediction. We confirm this by training models only on data from the most important regions. The limited change in performance suggests that we can adopt this strategy to identify the sensor placement efficiently.

VI. Conclusion

We developed a methodology based on machine learning for detecting gait abnormalities using plantar pressure data. Our approach involves pasteables, providing wearable biomedical sensors in a stick-and-peel form factor. We demonstrated a methodology for pasteable design without requiring *a priori* user studies through application of ML on publicly available

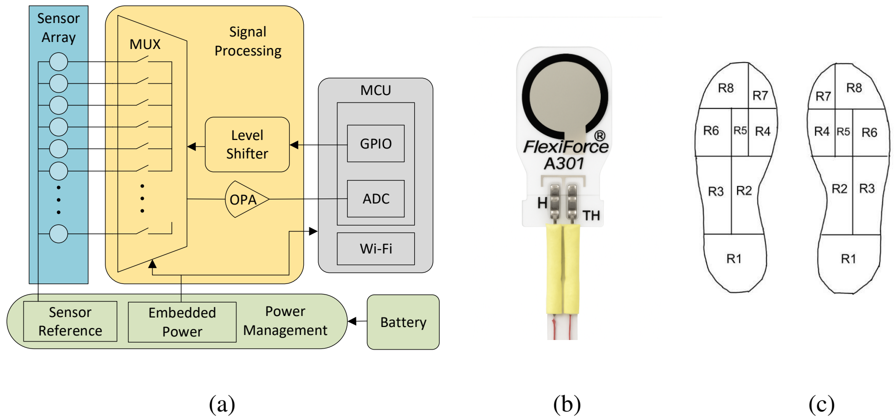


Fig. 7: Pasteable Design and Placement. (a) Hardware Components of Pasteable. (b) Pasteable Form Factor. It can be attached on the foot or insole like a band-aid. (c) Plantar Pressure Regions for Pastable Placement

datasets to identify in advance the ML models and monitorable parameters and built a pasteable prototype. Our results suggest that continuous monitoring with pasteables can provide a viable approach for gait monitoring reducing and eventually eliminating the need for current expensive laboratory setups.

In future work, we will develop more physical prototypes and explore sensor fusion with EMG and IMU modalities to improve detection accuracy. We will also conduct comprehensive user studies for validation in real-world conditions. Finally, We will explore opportunities for other applications of similar pasteable-based solutions.

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