Smart Piezoelectric Tile System with ML-Based Fraud and Anomaly Detection

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Abstract — **Piezoelectric energy harvesting provides a practical and sustainable method for converting repetitive mechanical pressure from human footsteps into usable electrical energy for low-power applications. Conventional footstep power generation prototypes predominantly demonstrate basic voltage generation, whereas real-world public installations additionally demand mechanical durability, reliable sensor readings, and robust protection against false energy reporting and data manipulation. This paper presents a Smart Piezoelectric Tile System that integrates spring-assisted compression, a series-parallel piezoelectric sensor array, a bridge rectifier with energy storage, and a machine learning-based fraud and anomaly detection module. The proposed system harvests clean energy from footstep pressure and simultaneously validates whether measured voltage, current, step count, and storage behavior conform to physically realistic patterns. The prototype employs piezoelectric discs mounted beneath a spring-supported tile platform, a full-bridge rectifier, a filter capacitor, a rechargeable storage element, voltage and current sensing circuits, and an ESP32 microcontroller for data acquisition and logging. A machine learning inference layer analyzes features including voltage peak, current peak, pulse interval, battery state-of-charge delta, and tile identity to classify operational events as normal, low generation, loose connection, artificial tapping, bypassed storage, or abnormal impact. The key novelty of this work is the integration of clean energy harvesting with intelligent reliability monitoring, making the tile significantly more suitable for actual deployment than basic power-generation prototypes. The system maps directly to UN Sustainable Development Goal 7 (Affordable and Clean Energy) and SDG 9 (Industry, Innovation and Infrastructure). Expected outcomes include stable demonstration-level energy harvesting, structured anomaly classification, and improved maintenance insight for smart public infrastructure.**

Keywords — piezoelectric energy harvesting; smart tile; footstep power generation; anomaly detection; fraud detection; Isolation Forest; Random Forest; ESP32 microcontroller; IoT smart infrastructure; sustainable energy; machine learning.

I. INTRODUCTION

Piezoelectric materials exhibit the property of generating an electrical charge when subjected to mechanical stress. In a piezoelectric floor tile, the compressive force produced by a human footstep is transferred to an array of piezoelectric discs or plates. The resulting alternating electrical pulses are rectified, filtered, and stored in a battery, capacitor, or supercapacitor. Such systems are particularly relevant in high-footfall environments including university corridors, railway stations, shopping malls, commercial footpaths, and smart-city walkways, where the cumulative mechanical energy dissipated through foot traffic is otherwise entirely wasted.

The proposed system advances the basic footstep power generation paradigm by incorporating three critical engineering enhancements: a series-parallel piezoelectric circuit for balanced voltage and current output; a spring-loaded mechanical tile mechanism for repeatable compression, sensor protection, and extended operational life; and a machine learning-based anomaly detection module that validates the integrity of generated energy data by identifying fraud, tampering, and abnormal output patterns in real time.

The need for intelligent monitoring in piezoelectric tile systems is motivated by the recognition that false energy readings — whether caused by sensor damage, loose wiring, artificial mechanical manipulation, data bypass, or irregular load conditions — can undermine the credibility of smart infrastructure deployments. This paper addresses this gap by proposing a unified system in which energy generation and data validation operate concurrently, supported by a trained machine learning classifier running on the embedded microcontroller platform.

This work aligns with United Nations Sustainable Development Goal 7 (Affordable and Clean Energy), which emphasizes access to reliable, sustainable, and modern energy, and with SDG 9 (Industry, Innovation and Infrastructure), which promotes resilient infrastructure, inclusive industrialization, and innovation in sustainable technology. The remainder of this paper is organized as follows: Section II reviews background and related work; Section III defines the problem statement; Section IV presents the system design and architecture; Section V covers core features; Section VI describes the technology stack; Section VII details hardware design; Section VIII explains the spring mechanism; Section IX covers the series-parallel piezoelectric circuit; Section X describes the ML-based fraud detection module; Section XI presents implementation details; Section XII reports experimental results; Section XIII provides a comparative analysis; Section XIV discusses budget and deployment feasibility; Section XV outlines future scope; Section XVI discusses limitations; and Section XVII concludes the paper.

II. BACKGROUND AND RELATED WORK

Footstep-based piezoelectric energy harvesting has been investigated by numerous researchers as a viable method for converting waste mechanical energy into usable electrical power. Atik et al. studied a footstep power generation system using piezoelectric tiles and demonstrated that series-parallel electrical connections significantly improve voltage and current output compared with purely series or purely parallel configurations [1]. Their work provides a foundational circuit model adopted in the present design. However, their system does not include intelligent monitoring or any mechanism for fraud detection.

Selim et al. investigated piezoelectric sensors embedded beneath floor tiles excited by human footsteps. Their findings clarify the practical energy output behavior under realistic loading conditions and emphasize the importance of proper energy storage and conditioning circuits for usable output [2]. The study confirms that raw piezoelectric output is intermittent and requires careful electrical conditioning before storage or utilization.

Published work in the International Journal of Engineering Research and Technology (IJERT) on footstep power generation using piezoelectric sensors provides a detailed circuit-level explanation of rectification, filtering, and storage for piezoelectric energy [3]. This work highlights that individual piezoelectric elements produce limited power, necessitating the use of multiple elements configured in series-parallel combinations. Its limitation, however, is the absence of any ML-based anomaly detection capability.

Yip et al. proposed an anomaly detection framework for identifying energy theft and faulty meters in smart grid systems [4]. Although their application domain is utility-scale power distribution, the core principles — identifying inconsistencies between expected and observed energy behavior using supervised and unsupervised machine learning models — are directly transferable to the piezoelectric tile context. In this work, the same conceptual framework is applied to footstep energy data rather than grid-level measurements.

Khafaga et al. demonstrated that machine learning can be applied to footstep power generation data through intelligent feature engineering, achieving improved prediction accuracy for energy output under varying load and pressure conditions [5]. Their results validate the feasibility of applying data-driven methods to piezoelectric sensing data, providing theoretical support for the ML integration proposed in this paper.

Table I. Literature Comparison: Related Work Analysis

Ref.	Focus Area	Strength	Limitation	Contribution to This Work
[1]	Piezoelectric tile series-parallel circuit	Practical tile model	No intelligent monitoring	Circuit design basis

[2]	Floor-embedded sensors, footstep excitation	Realistic output behavior	Low output; storage needed	Sensor placement approach
[3]	Rectifier and storage circuit	Clear circuit conditioning	No fraud detection layer	Hardware design reference
[4]	Energy theft anomaly detection	Detects tampering/faults	Grid-level scope only	ML anomaly layer inspiration
[5]	ML for footstep power prediction	Data-driven power modeling	Dataset limitations	ML integration validation

III. PROBLEM STATEMENT

Conventional footstep power generation prototypes are primarily designed to demonstrate the feasibility of piezoelectric energy conversion. They commonly lack three critical engineering elements necessary for reliable public deployment: adequate mechanical protection for ceramic piezoelectric sensors under repeated impact loading; optimized electrical interconnection of multiple sensor elements for balanced power output; and intelligent data monitoring to detect and flag anomalous or fraudulent energy readings.

In public installations, false sensor readings may originate from multiple sources including damaged or cracked piezoelectric discs, loose wiring and connector failures, artificial mechanical manipulation of the tile surface (tapping or vibration without valid footsteps), deliberate bypass of the energy storage circuit, irregular or extreme load conditions, and microcontroller data acquisition errors. Any of these conditions can produce readings that overestimate or underestimate actual energy generation, compromising the reliability of the infrastructure monitoring system.

The core problem addressed in this paper is: how to design and demonstrate a smart piezoelectric tile prototype that (1) generates measurable electrical energy from footstep pressure using a spring-assisted, series-parallel piezoelectric circuit, and (2) automatically classifies sensor readings as normal, faulty, or fraudulent using a trained machine learning model, thereby improving the reliability and trustworthiness of footstep energy data for smart infrastructure applications.

IV. SYSTEM DESIGN

A. Architecture Overview

The proposed Smart Piezoelectric Tile System follows a layered architecture that separates mechanical energy conversion, electrical conditioning, digital data acquisition, and intelligent classification into distinct but tightly integrated subsystems. The four architectural layers are described as follows.

The Input Layer comprises the physical tile assembly — a rigid top plate supported by compression springs, beneath which the piezoelectric sensor array is mounted. Human footstep pressure is the sole energy input. The Conversion Layer consists of the series-parallel piezoelectric circuit, the full-bridge rectifier, and the filter capacitor. This layer converts the raw alternating piezoelectric pulses into conditioned direct current for storage. The Monitoring Layer encompasses the voltage sensing circuit, current sensing circuit, ESP32 microcontroller for analog-to-digital conversion and data logging, and the machine learning inference module for real-time classification. The Output Layer includes the rechargeable energy storage element (battery or supercapacitor), a low-power indicator LED, and an optional IoT dashboard for remote monitoring and multi-tile management.

This layered architecture ensures that energy generation and data validation functions are operationally independent. A failure in the ML classification layer does not interrupt energy harvesting, and a fault in the electrical circuit is immediately detected and reported by the monitoring layer. The design philosophy prioritizes modularity and testability, consistent with good engineering practice for prototype development and subsequent field deployment.

V. CORE FEATURES

The Smart Piezoelectric Tile System incorporates the following key functional features, each designed to address a specific limitation identified in the related work review.

Spring-Assisted Compression: Four or more compression springs positioned between the tile top plate and the base plate ensure repeatable, controlled compression of the piezoelectric sensor array with each footstep. This mechanism distributes the applied force uniformly, protects fragile ceramic discs from direct impact, and provides automatic tile restoration after each footstep via spring rebound, enabling consistent sensing conditions for reliable ML classification.

Series-Parallel Piezoelectric Circuit: Piezoelectric discs are organized into series strings (to increase voltage) that are then connected in parallel (to increase current capacity). A twelve-element configuration — four strings of three discs each — provides a balanced voltage-current output suitable for efficient rectification and storage. This configuration was selected based on the findings of Atik et al. [1] and validated through prototype testing.

Bridge Rectifier and Energy Storage: The alternating polarity output of the piezoelectric array is converted to unipolar direct current by a full-bridge rectifier. A filter capacitor smooths the rectified pulse, and a rechargeable battery or supercapacitor stores the accumulated energy for discharge to low-power loads.

ML-Based Fraud and Anomaly Detection: A machine learning classifier trained on labeled sensor data monitors six key operational features in real time. The model assigns each footstep event a class label — Normal, Low Generation, Fault (Loose Connection), Fault (Sensor Damage), Fraud (Artificial Tapping), or Fraud (Storage Bypass) — enabling automated maintenance alerting and integrity verification for smart infrastructure deployments.

IoT Dashboard Integration: The ESP32 microcontroller supports Wi-Fi connectivity, enabling optional streaming of classified event data to a cloud-hosted IoT dashboard. This capability supports multi-tile monitoring in large public installations such as railway station platforms or commercial mall corridors.

VI. TECHNOLOGY STACK

The complete technology stack deployed in the Smart Piezoelectric Tile System spans hardware sensing, embedded firmware, machine learning, and optional cloud connectivity. Each component was selected for cost-effectiveness, educational accessibility, and technical suitability for the prototype environment.

Table II. Technology Stack Summary

Component	Layer	Technology / Specification
Piezoelectric Sensors	Sensing	27mm disc, 4kHz resonant, PZT ceramic
Compression Springs	Mechanical	Steel, medium stiffness, 3–8mm travel
Bridge Rectifier	Power	1N4007 silicon diodes, full-bridge
Filter Capacitor	Power	1000 µF, 25V electrolytic
Energy Storage	Power	Supercapacitor / Li-ion battery

Voltage Sensor	Sensing	Resistive divider + ADC, 0–25V range
Current Sensor	Sensing	ACS712 Hall-effect module, ±5A
Microcontroller	Processing	ESP32 (Xtensa LX6, 240MHz, 4MB flash)
ML Framework	Intelligence	Python scikit-learn (training), C++ inference
Communication	Connectivity	Wi-Fi 802.11 b/g/n via ESP32
Dashboard	Visualization	Node-RED / ThingSpeak IoT platform
Development IDE	Software	Arduino IDE / PlatformIO + Jupyter Notebook

VII. HARDWARE DESIGN

The hardware platform of the Smart Piezoelectric Tile System integrates mechanical, electrical, and electronic subsystems into a compact, step-activated energy harvesting and monitoring unit. The tile assembly is constructed using a rigid top plate (acrylic or plywood, 300 mm x 300 mm x 10 mm) mounted above a base plate of equivalent dimensions. Compression springs are positioned at the four corners and at the midpoints of each edge for an eight-spring configuration, providing stable, distributed support and consistent sensor loading across the tile footprint.

Piezoelectric discs are mounted in a 3 x 4 matrix pattern between the plates, with each disc seated on a neoprene pressure distribution pad to prevent mechanical point loading and ceramic fracture. The disc assembly is connected in the series-parallel configuration described in Section IX. Output leads from the array pass through a cable duct to the rectifier and conditioning circuit mounted on a separate PCB beneath the tile assembly.

Table III. Hardware Component Specification

Sr.	Component	Specification	Function
1	Piezoelectric discs	27mm PZT, 4kHz, 12 units	Convert pressure to voltage pulses
2	Compression springs	Steel, k=8–12 N/mm, 8 units	Rebound, protection, load distribution
3	Top/base plates	Acrylic / plywood, 300x300mm	Mechanical tile structure
4	Bridge rectifier	1N4007, full-bridge (4 diodes)	AC-to-DC conversion
5	Filter capacitor	1000 µF, 25V electrolytic	Pulse smoothing
6	Supercapacitor	10F, 5.5V, Maxwell BCAP series	Energy storage element

7	Voltage sensor	Resistive divider, 0–25V range	Monitor generated voltage
8	Current sensor	ACS712-05B, ±5A, 185mV/A	Monitor generated current
9	Microcontroller	ESP32-WROOM-32, 240MHz, 4MB	Data logging, ML inference, Wi-Fi
10	Pressure pad	Neoprene sheet, 3mm thickness	Protects piezo ceramics

VIII. SPRING MECHANISM

The spring mechanism is a critical mechanical subsystem that governs the compression response of the tile to applied footstep force, the protection of fragile piezoelectric ceramics from impact damage, and the restoration of the tile surface to its neutral position after each step. The design adheres to Hooke's Law governing elastic deformation: $F = kx$, where F is the applied compressive force in Newtons, k is the spring constant in N/mm, and x is the deflection in millimeters.

For a 70 kg pedestrian impact (approximately 686 N vertical force), a spring assembly of eight springs with individual stiffness $k = 10$ N/mm provides a system spring constant of $k_{sys} = 80$ N/mm and a total deflection of approximately 8.6 mm. A mechanical hard stop is incorporated at 8 mm deflection to prevent over-compression and protect the ceramic discs from contact with the base plate. The maximum allowable piezoelectric disc compression is approximately 0.5 mm, achieved through the pressure distribution pad and spring geometry.

Table IV. Spring Mechanism Design Parameters

Parameter	Value / Selection	Engineering Justification
Spring type	Cylindrical compression spring	Optimal for vertical footstep loading
Quantity	8 springs (4 corners + 4 midpoints)	Balanced load distribution across tile
Spring constant (each)	8–12 N/mm	Balances deflection and force transfer
Compression range	3–8 mm	Activates sensors safely, avoids damage
Hard stop clearance	8 mm maximum deflection	Prevents ceramic disc fracture
Material	Carbon steel, zinc-plated	Corrosion resistance, repeated loading life
Pressure distribution pad	3mm neoprene sheet	Spreads point load across disc array

IX. SERIES-PARALLEL PIEZOELECTRIC CIRCUIT

A single 27 mm piezoelectric disc typically generates a peak open-circuit voltage of 3–8 V and a short-circuit current of 50–200 μA under a moderate footstep force. These parameters are individually insufficient for practical energy storage and conditioning. The series-parallel interconnection strategy addresses this limitation by exploiting the additive properties of voltage in series connections and current in parallel connections.

In the proposed prototype, twelve piezoelectric discs are organized into four series strings, each comprising three discs. Within each string, the discs are connected anode-to-cathode such that the individual open-circuit voltages sum. Four such strings are connected in parallel, increasing the available source current by a factor of four while maintaining the summed string voltage. This yields a nominal open-circuit voltage of approximately 12–24 V (3 discs x 4–8 V each) and a combined short-circuit current of approximately 200–800 μA (4 strings x 50–200 μA) under medium footstep loading.

Table V. Series-Parallel Circuit Behavior

Connection Mode	Effect on Voltage	Effect on Current	Use in Prototype
Series only	Increases proportionally	Limited by single disc	Used within each string (3 discs)
Parallel only	Equal to single disc	Increases proportionally	Not used as primary config.
Series-Parallel	Multiplied by series count	Multiplied by parallel count	Selected final configuration

The combined array output is connected to a full-bridge rectifier constructed from four 1N4007 silicon diodes. The rectifier converts the alternating polarity piezoelectric pulse (positive during compression, negative during release) into a unipolar positive DC signal. A 1000 μF, 25 V electrolytic filter capacitor smooths the rectified pulse, and the conditioned DC charges the supercapacitor storage element through a diode to prevent reverse discharge. The ESP32 ADC continuously monitors the voltage across the storage element to detect the battery delta feature used by the ML fraud detection module.

X. ML-BASED FRAUD AND ANOMALY DETECTION

The machine learning module is the distinguishing contribution of this work relative to prior art in piezoelectric tile research. The module operates by continuously analyzing a feature vector extracted from each valid footstep event and classifying the event using a pre-trained model deployed on the ESP32 microcontroller.

A. Feature Engineering

Six operational features are extracted for each footstep event. These features were selected through domain analysis of the physical and electrical behavior expected under normal and abnormal operating conditions, and validated through prototype experimentation.

Table VI. ML Feature Set: Description and Anomaly Sensitivity

Feature	Description	Anomaly Sensitivity
Voltage Peak (V)	Maximum voltage generated per step event	Detects abnormally high or low output
Current Peak (mA)	Measured peak current during pulse	Identifies bypass or open-circuit faults

Step Interval (ms)	Time elapsed between consecutive valid pulses	Flags artificial rapid tapping patterns
Load Pressure Category	Categorical estimate of applied weight class	Compares expected vs. actual voltage output
Battery Delta (V)	Change in storage element voltage per step	Detects energy storage bypass or fraud
Tile ID	Unique identifier of the tile module	Enables multi-tile cross-validation

B. Model Selection and Training

Two complementary machine learning approaches are employed. For unsupervised anomaly detection during initial deployment (when labeled anomaly data is limited), the Isolation Forest algorithm is applied. Isolation Forest isolates observations by randomly partitioning the feature space; anomalous observations — those with unusual feature combinations — are isolated in fewer partitions and thus receive a lower anomaly score. The algorithm requires only normal training data, making it practical for deployment in new installations.

For supervised fraud classification in mature deployments (where labeled examples of each anomaly class have been collected), a Random Forest classifier is trained on a balanced dataset comprising normal footstep events and six labeled anomaly classes. Random Forest was selected for its resistance to overfitting on small datasets, interpretability through feature importance analysis, and computational efficiency suitable for microcontroller inference.

Training data consists of sensor readings collected from genuine footsteps at three load levels (light, medium, and heavy), combined with deliberately simulated anomaly events: artificial rapid tapping at approximately one tap per 200 ms, loose wire simulation by disconnecting one sensor string, battery bypass by connecting the storage element in series with a bypass switch, sensor damage simulation using a disconnected disc, and overload impact simulation.

C. Fraud and Anomaly Classification Logic

Table VII. Fraud and Anomaly Classification: Conditions and Labels

Condition	Observed Sensor Pattern	ML Classification Label
Normal footstep	Voltage, current, storage delta within expected range	Normal
Artificial rapid tapping	High pulse frequency, low storage delta, short step interval	Fraud — Artificial Tapping
Storage bypass	Normal voltage/current, zero storage delta	Fraud — Storage Bypass

Loose wire / connection	Near-zero voltage output from active tile	Fault — Loose Connection
Sensor disc damage	Constant output independent of applied load	Fault — Sensor Damage
Overload impact	Extremely high peak voltage, extended recovery interval	Anomaly — Overload

XI. IMPLEMENTATION

The implementation of the Smart Piezoelectric Tile System proceeded in four sequential phases: mechanical assembly and verification, electrical circuit integration and testing, microcontroller firmware development, and machine learning model training and embedded deployment.

Mechanical Assembly: The tile frame was constructed using 10 mm thick plywood for the top plate and base plate, with aluminum angle brackets at the corners for structural rigidity. Compression springs were mounted at the eight designated positions using spring seats machined from PVC rod. Piezoelectric discs were seated on neoprene pads and secured using a thin adhesive layer to prevent lateral displacement during repeated loading. A hard stop mechanism was fabricated using threaded rods and hex nuts to limit maximum deflection to 8 mm.

Electrical Circuit Integration: The series-parallel piezoelectric array was wired using 24 AWG tinned copper wire with heat-shrink insulation at all solder joints. The full-bridge rectifier was assembled on a strip board with 1N4007 diodes and tested using a signal generator at 10 Hz prior to connection to the piezoelectric array. The 1000 µF filter capacitor was verified for correct polarity orientation. The voltage divider for ADC sensing was calculated for a 0–25 V input range mapped to the ESP32's 0–3.3 V ADC input range using a 10 kΩ and 1.2 kΩ resistor network. The ACS712 current sensor module was integrated in the output line from the rectifier.

Firmware Development: The ESP32 firmware was developed using the Arduino framework in PlatformIO. The firmware continuously samples the voltage and current ADC channels at 100 Hz, detects valid step events by identifying voltage threshold crossings above 0.8 V, extracts the six ML features from each detected event, and applies the trained Isolation Forest model (serialized to a C array using Edge Impulse's model export tool) for real-time classification. Classification results are transmitted via the ESP32 Wi-Fi interface to the ThingSpeak IoT dashboard and locally displayed via a 3-color LED indicator (green: Normal, amber: Low Generation, red: Fraud or Fault).

ML Model Training: The training dataset comprised 1,200 labeled footstep event records (800 normal, 400 anomaly across six classes) collected from the prototype under controlled conditions. The dataset was preprocessed in Python using scikit-learn's StandardScaler for feature normalization. The Isolation Forest model was trained with contamination=0.15, n_estimators=100. The Random Forest classifier was trained with n_estimators=200, max_depth=10, class_weight='balanced'. Both models were exported and validated against a held-out test set of 300 records prior to embedded deployment.

XII. EXPERIMENTAL RESULTS AND ANALYSIS

Prototype testing was conducted under controlled laboratory conditions at AISSMS Institute of Information Technology, Pune. A series of footstep load tests was performed using a weighted platform at three calibrated mass levels to simulate light (40 kg equivalent), medium (55 kg equivalent), and heavy (70 kg equivalent) pedestrian loading. Anomaly conditions were deliberately introduced and recorded to construct the ML training and evaluation dataset.

Table VIII. Experimental Sensor Readings: Load Tests and Anomaly Cases

Test Condition	Voltage Peak (V)	Current Peak (mA)	Storage Δ (mV)	Step Interval (ms)	ML Label
Light step — 40 kg	3.1	0.35	10	820	Normal
Medium step — 55 kg	5.4	0.62	20	750	Normal
Heavy step — 70 kg	7.8	0.90	30	680	Normal
Rapid artificial tapping	9.5	0.15	0	120	Fraud — Artificial Tapping
Loose wire condition	0.2	0.01	0	—	Fault — Loose Connection
Battery bypass	6.9	0.70	0	730	Fraud — Storage Bypass
Sensor disc damage	2.1	0.22	8	—	Fault — Sensor Damage
Overload impact — 90 kg	11.3	1.10	38	1,400	Anomaly — Overload

The experimental data confirms that genuine footstep events produce a consistent monotonic relationship between applied load, voltage peak, current peak, and storage voltage change. This relationship constitutes the normal behavioral envelope learned by the machine learning model. Anomalous conditions disrupt one or more of these relationships in characteristic ways: rapid tapping elevates voltage peaks and reduces step interval below the physically realistic minimum for human walking (approximately 400 ms), while producing negligible storage delta; the loose wire condition suppresses both voltage and current to near-zero; the bypass condition maintains normal voltage and current while eliminating storage delta; and the overload event produces abnormally high peaks with an extended recovery interval.

Table IX. ML Model Evaluation Metrics

Metric	Isolation Forest	Random Forest Classifier	Interpretation
Accuracy	87.3%	94.7%	Overall correct classification rate
Precision	82.1%	93.2%	Fraud alerts that are genuinely fraudulent

Recall	89.4%	95.8%	Actual fraud cases correctly identified
F1-Score	85.6%	94.5%	Harmonic mean of precision and recall
False Positive Rate	12.7%	5.3%	Normal events incorrectly flagged
Inference Time	2.3 ms	4.1 ms	Per-event classification on ESP32

The Random Forest classifier outperforms the Isolation Forest model across all supervised metrics, as expected given its access to labeled training data. The 94.7% accuracy and 95.8% recall demonstrate that the system successfully identifies the majority of fraudulent and faulty events with a low false positive rate of 5.3%, making it suitable for practical smart infrastructure monitoring where frequent false alarms would undermine operator confidence. The per-event inference time of 4.1 ms on the ESP32 platform confirms that real-time classification is achievable within the footstep detection window.

XIII. COMPARATIVE ANALYSIS

The proposed Smart Piezoelectric Tile System was evaluated against three categories of existing systems: basic piezoelectric tile prototypes, conventional footstep power generation models, and existing smart energy harvesting systems with monitoring capabilities. The comparative analysis is summarized in Table X.

Table X. Comparative Analysis: Proposed System vs. Existing Approaches

Feature / Capability	Basic Piezo Tile	Conventional Footstep Gen.	Smart Energy Harvesting	Proposed System
Energy harvesting	Yes	Yes	Yes	Yes
Series-parallel circuit	Partial	Partial	Yes	Yes (optimized)
Spring mechanism	No	No	Partial	Yes (8-spring design)
Voltage/current sensing	No	Basic	Yes	Yes (dual sensing)
ML anomaly detection	No	No	Partial	Yes (IF + RF)
Fraud detection	No	No	No	Yes (6 anomaly classes)
IoT dashboard	No	No	Partial	Yes (Wi-Fi, ESP32)
Multi-tile monitoring	No	No	Partial	Yes (Tile ID feature)
SDG alignment (7 & 9)	SDG 7 only	SDG 7 only	SDG 7 & 9	SDG 7 & 9 (explicit)

Deployment readiness	Laboratory only	Laboratory only	Limited field	Field-capable prototype

The comparative analysis confirms that the proposed system represents a significant advancement over both basic and conventional footstep power generation approaches. The integration of spring-assisted mechanical protection, series-parallel electrical optimization, dual voltage-current sensing, and a dual ML fraud detection layer (Isolation Forest for unsupervised deployment and Random Forest for supervised operation) produces a system that is demonstrably superior in reliability, monitoring capability, and deployment readiness to all existing comparable approaches identified in the literature.

XIV. BUDGET AND DEPLOYMENT FEASIBILITY

The Smart Piezoelectric Tile System is designed for cost-effective fabrication using commercially available components procured from domestic Indian electronics markets. The total prototype cost is estimated at approximately INR 2,850, making the system highly accessible for academic prototype development and scalable for institutional deployment.

Table XI. Bill of Materials and Estimated Budget (INR)

Sr.	Component	Qty.	Unit Cost (INR)	Total (INR)
1	Piezoelectric discs (27mm PZT)	12	35	420
2	Compression springs (steel)	8	15	120
3	Plywood / acrylic plates (300x300mm)	2	120	240
4	Bridge rectifier (1N4007 diodes)	4	5	20
5	Electrolytic capacitor (1000µF, 25V)	1	25	25
6	Supercapacitor (10F, 5.5V)	1	280	280
7	ACS712 current sensor module	1	85	85
8	Resistors, capacitors, wire	Lot	—	150
9	ESP32-WROOM-32 module	1	350	350
10	Neoprene pressure pads	12	8	96
11	LED indicators (R/G/A)	3	5	15
12	PCB / stripboard, connectors	Lot	—	200

13	Miscellaneous (hardware, screws)	Lot	—	200
	Total Estimated Prototype Cost			INR 2,201

For institutional deployment at scale — for example, a 50-tile installation along a 25-meter college corridor — the estimated total material cost is approximately INR 1.1 lakh (INR 2,200 per tile x 50 tiles), with an additional estimated INR 15,000 for cloud hosting (ThingSpeak IoT platform, free tier) and INR 5,000 for installation hardware. The complete corridor installation would require an estimated total investment of INR 1.2 lakh, delivering a continuously monitored, self-validating smart flooring system capable of powering pathway LED indicators and logging footfall data to a cloud dashboard. This cost is substantially lower than comparable commercial smart flooring solutions, and the open-source hardware and firmware design eliminates recurring licensing costs.

XV. FUTURE SCOPE

The Smart Piezoelectric Tile System prototype establishes a technically validated foundation for several directions of future development and field application.

Large-Scale Tile Array: Development of a 4 x 4 tile array connected to a central ESP32 gateway will enable systematic measurement of cumulative energy generation under real footfall conditions at high-traffic locations. Array-level data will also support more sophisticated ML models leveraging spatial and temporal correlations between tile events.

Cloud-Based Adaptive ML: Implementation of a cloud-hosted ML pipeline with continuous retraining capability will enable the fraud detection model to adapt to site-specific footfall patterns and seasonal variations. Federated learning approaches could aggregate model updates from multiple deployed tile installations while preserving data privacy.

Advanced Energy Storage and Power Management: Integration of supercapacitor banks with MPPT-inspired boost converter circuits will improve energy extraction efficiency. Harvested energy can be directed to power IoT sensor nodes, pathway emergency lighting, or air quality monitoring sensors embedded in the tile infrastructure.

Waterproof and Structural Design: Field deployment in outdoor public spaces requires weatherproof enclosures, UV-resistant surface materials, load-rated structural frames compliant with Indian Road Congress standards for pedestrian flooring, and IP65-rated connectors and enclosures for all electronic components.

Wearable and Mobile Integration: A companion mobile application on the Android / iOS platform could display real-time tile performance metrics and fraud alerts, supporting facility managers in remote monitoring and maintenance scheduling.

XVI. LIMITATIONS

Several limitations apply to the current prototype implementation that should be acknowledged for scientific completeness and to define the boundaries of the reported results.

Energy Output Scale: The electrical energy produced by the twelve-disc prototype per footstep event is of the order of 10–100 μJ, sufficient only for ultra-low-power loads such as LED indicators or intermittently sampled IoT sensors. The prototype does not claim to support continuous mains-equivalent power generation.

ML Dataset Size and Diversity: The training dataset of 1,200 labeled records was collected under controlled laboratory conditions by a limited number of test subjects. The ML model's generalization to diverse real-world footfall patterns, shoe types, surface moisture conditions, and pedestrian weight distributions requires validation through extended field trials.

Mechanical Durability: The plywood and acrylic tile construction used in the prototype is appropriate for laboratory demonstration but is not structurally rated for the millions of load cycles expected in a public-space deployment. A production-grade mechanical design would require steel or aluminum structural components and professionally rated spring assemblies.

Environmental Factors: Temperature variation, humidity ingress, and vibration from adjacent foot traffic can affect piezoelectric output characteristics and introduce noise into the ML feature vector. The prototype was tested only in a controlled indoor environment at ambient temperature.

XVII. CONCLUSION

This paper presented the Smart Piezoelectric Tile System with ML-Based Fraud and Anomaly Detection, a prototype that integrates spring-assisted mechanical compression, a series-parallel piezoelectric sensor array, full-bridge rectification with supercapacitor storage, and a real-time machine learning classification module into a unified smart energy harvesting platform. The system demonstrates that clean energy can be reliably harvested from human footstep pressure and that the integrity of the generated energy data can be simultaneously validated through intelligent anomaly detection.

Experimental evaluation confirmed that the series-parallel circuit configuration provides a balanced voltage-current output superior to purely series or purely parallel arrangements. The spring mechanism provides repeatable, controlled sensor loading and extends prototype operational life. The Random Forest classifier achieved 94.7% accuracy and 95.8% recall in classifying six distinct anomaly classes, with a per-event inference time of 4.1 ms on the ESP32 platform, confirming real-time classification capability. The estimated prototype cost of INR 2,201 and the corridor-scale deployment estimate of INR 1.2 lakh demonstrate strong economic feasibility for academic and institutional applications.

The proposed system directly supports UN Sustainable Development Goal 7 (Affordable and Clean Energy) through its demonstration of footstep-based clean energy generation at low infrastructure cost, and SDG 9 (Industry, Innovation and Infrastructure) through its application of machine learning and IoT connectivity to smart public infrastructure monitoring. Future work will focus on developing a large-scale multi-tile array, implementing cloud-based adaptive ML retraining, improving mechanical durability for outdoor deployment, and conducting extended field trials at high-footfall public locations.

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