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HYBRID REGRESSION APPROACH FOR PREDICTION OF RENEWABLE ENERGY FROM HUMAN FOOTSTEP POWER SYSTEMS

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ABSTRACT

The increasing global emphasis on renewable and sustainable energy sources has driven researchers to explore innovative methods of power generation. Footstep power harvesting, which utilizes human walking motion to generate electricity, offers a promising avenue for powering low-energy devices in smart cities and IoT applications. According to recent studies, an average adult produces between 3–8 W of instantaneous mechanical power per step, and large-scale foot traffic in urban areas can potentially yield over 500 kWh annually from a single busy location. However, accurately predicting the electrical output from such systems remains a challenge due to variations in human weight, walking patterns, and environmental factors. Existing methods, including the Huber Regressor and Support Vector Regression (SVR), provide reasonable predictions but often struggle with capturing the complex nonlinear relationships between input parameters such as voltage (V), current (μA), weight (kg), location, and resulting power (mW). These traditional approaches are also sensitive to outliers and fail to fully exploit patterns in multidimensional datasets, leading to suboptimal forecasting accuracy. To address these limitations, this study proposes a hybrid deep learning–machine learning framework combining a Feed Forward Neural Network (FFNN) with an Extra Tree Regressor (ETR) to enhance prediction reliability. The methodology begins with rigorous data preprocessing, including normalization of numerical features, one-hot encoding of the categorical location attribute, and outlier detection to improve model robustness. The existing Huber Regressor and SVR models are implemented as benchmark baselines to assess comparative performance. The proposed FFNN-ETR model leverages the FFNN's capability to learn intricate feature interactions and nonlinear dependencies, while the ETR enhances prediction stability through ensemble-based decision boundaries. This dual-stage approach not only achieves superior accuracy but also improves resistance to noise and environmental variability in footstep energy harvesting datasets.

Key words: Human Footstep Power, Energy Harvesting, Smart Energy Systems, IoT-based Energy Monitoring

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1. INTRODUCTION

Urban foot traffic and human movement represent a largely untapped reservoir of renewable energy potential. Studies indicate that in densely populated environments, small amounts of electricity generated from footsteps—often just a few milliwatts—can accumulate significantly, especially when deployed at scale across transit hubs or high-traffic zones. For instance, the company Pavegen demonstrated that embedding energy-harvesting tiles across just 3.1% of a high-footfall floor area could yield 1.1 MWh per year—equivalent to approximately 0.5% of the building's annual energy requirements. Experimental prototypes underscore both the feasibility and the limitations of footstep energy systems. One low-cost setup managed to generate up to 6.9 watts per step, delivering a surprisingly robust yield given its simplicity. In another study using piezoelectric tiles, individual footsteps produced up to 249.6 milliwatts, which was enough to light a pair of LEDs and operate micro-device. While modest, these outputs are noteworthy considering they stem from mere human gait—an activity ubiquitous in public spaces worldwide. Harnessing pedestrian motion to produce electricity aligns perfectly with the ethos of sustainable energy and smart city design. Footstep energy harvesting systems can transform infrastructures—sidewalks, subway stations, staircases—into living power-generating networks. This approach not only leverages otherwise wasted energy but also introduces locally generated power, potentially reducing reliance on traditional grids and improving resilience in urban energy ecosystems. The escalating global energy demand, coupled with the depletion of non-renewable resources, necessitates the exploration of alternative energy sources. Footstep energy harvesting presents a promising solution by converting human kinetic energy into electrical power. For instance, companies like Pavegen have developed flooring tiles that generate electricity from footsteps, offering a sustainable energy source in urban environments.

2. LITERATURE SURVEY

Babu et al. [6] proposed a footpath-based power generation system utilizing the Piezoelectric Effect (PZE) to convert mechanical stress from pedestrian footsteps into electrical energy. Their methodology incorporated pressure-sensitive tiles connected to a power conditioning unit for efficient voltage regulation and storage. The study analyzed tile placement, pedestrian traffic flow, and generated voltage patterns to optimize energy capture. A prototype was developed to validate the real-time performance under varying load conditions, ensuring compatibility with small-scale electrical appliances. However, the system exhibited reduced energy conversion efficiency due to limitations in feature extraction from dynamic footstep pressure variations. Kumar et al. [7] presented a PZE-based energy harvesting mechanism designed to harness vibrations and mechanical deformations from various surfaces. The proposed model integrated piezoelectric sensors, an energy management circuit, and storage components to optimize power output under fluctuating mechanical loads. They emphasized material selection for high piezoelectric coefficient values and implemented a rectification stage to stabilize the generated voltage. Performance analysis demonstrated improved energy yield when deployed in high-vibration environments such as walkways and transportation platforms. Nonetheless, the approach suffered from inadequate feature selection techniques for optimizing sensor array configurations. Ghimire et al. [8] developed a piezoelectric cell-based power generation and storage architecture aimed at capturing kinetic energy from surface vibrations. Their design combined multiple piezoelectric layers with parallel-connected storage units to ensure continuous power supply. The researchers implemented a voltage regulation circuit to maintain steady output and analyzed the performance under different vibration intensities. Experimental results validated the feasibility for powering low-energy devices in urban environments. Despite its effectiveness, the methodology faced computational complexity issues during optimization of the multilayer arrangement for maximum energy yield. Luckie et al. [9] introduced a Distributed Acoustic Sensing (DAS) approach for detecting footstep-induced vibrations to support energy harvesting systems. The method utilized optical fiber sensors embedded beneath walking surfaces to capture precise vibration thresholds, which were processed to identify optimal points for energy conversion. The study addressed signal calibration, noise reduction, and spatial resolution enhancement to improve detection reliability. Field experiments demonstrated accurate vibration localization even in high-footfall areas. However, the system performance declined due to lower detection accuracy when handling multi-source vibration feature mapping. dos Santos et al. [10] proposed a PZT (Lead Zirconate Titanate)-based energy harvesting system for agricultural machinery, focusing on different sensor configurations and rectification methods. The design evaluated parallel and series PZT arrangements under mechanical excitation from machinery vibrations, aiming to maximize power output. A high-efficiency rectification circuit was incorporated to ensure minimal energy loss during conversion. Testing under field conditions revealed optimal configurations for sustained energy harvesting during prolonged operation. Nevertheless, the methodology experienced grading inaccuracies in evaluating performance across varying PZT configurations.

Chen et al. [11] presented a thermal modeling and stability analysis framework for a power generation cabin deployed in the Antarctica plateau. The approach accounted for extreme temperature fluctuations, insulation requirements, and heat dissipation constraints. A coupled thermal–electrical simulation was performed to assess system stability under varying load and environmental conditions. The model incorporated feedback-based thermal control to prevent efficiency degradation in sub-zero climates. Despite its robustness, the method encountered performance limitations due to lower precision in identifying critical thermal feature parameters affecting stability. Hu et al. [12] introduced a novel vitamin-based self-assembly piezoelectric structure for eco-friendly energy generation. The design utilized bio-compatible molecular structures arranged in a piezoelectric lattice to harvest mechanical energy. The self-assembled films were integrated with an energy storage module and tested for durability, voltage output, and bio-safety. Results indicated high flexibility, environmental sustainability, and competitive power output compared to synthetic piezoelectric materials. However, the approach exhibited reduced overall performance under complex multi-axis stress conditions due to insufficient optimization of structural feature alignment. Yadav et al. [13] proposed a SMART (Smart Multi-point Assisted Renewable Technology)-based multi-point matching approximation method for renewable interconnected power systems. The methodology integrated multi-point reference data matching with real-time load balancing to enhance grid stability. The algorithm utilized adaptive approximation functions for varying renewable energy inputs and ensured minimal power loss during transmission. Simulation studies demonstrated superior energy distribution efficiency across interconnected nodes. Nonetheless, the system was hindered by high computational complexity in matching algorithms during large-scale renewable integration scenarios. Pattnaik et al. [14] proposed intelligent strategies for techno-economic assessment of large-scale energy storage integrated hybrid power systems. The methodology involved integrating multiple renewable energy sources with large-capacity energy storage systems to ensure optimal power dispatch. They applied advanced optimization algorithms to minimize operational costs while maintaining supply reliability, considering both technical and economic constraints. The framework incorporated simulation-based decision-making to evaluate the trade-offs between storage capacity, renewable penetration, and system stability. However, the approach faced limitations in accurately extracting critical operational features under fluctuating renewable input conditions. Johar et al. [15] developed a Persistent Pulse Generator (PPG) for consistent signal generation across varying load conditions. The design utilized a combination of switching circuits, capacitive storage, and control modules to produce continuous pulses with minimal distortion. The system was evaluated for stability, voltage uniformity, and efficiency under different input power levels. Practical tests confirmed the generator's ability to maintain operational continuity in intermittent power scenarios. Nonetheless, the methodology exhibited performance degradation due to insufficient optimization in pulse feature calibration for high-frequency applications.

Garemark et al. [16] introduced a Salt-In-Wood Piezoelectric Power Generator (SIW-PEG) adopting a circular materials design for sustainable energy harvesting. The design infused salt ions into wood-based structures, enhancing piezoelectric performance without relying on synthetic materials. They analyzed mechanical durability, piezoelectric coefficient improvement, and eco-friendly scalability. Field tests demonstrated competitive power output and environmental benefits compared to traditional piezoelectric materials. However, the system underperformed in certain load cases due to lower feature resolution when mapping ionic distribution across the wood structure. Kumar et al. [17] presented a Brown Bear Optimized Random Forest (BBORF) model for short-term solar power forecasting. The model employed Brown Bear Optimization (BBO) for hyperparameter tuning of the Random Forest algorithm, enabling accurate solar irradiance prediction. The methodology considered meteorological datasets, seasonal variations, and cloud movement patterns for precise forecasting. Comparative results showed superior prediction accuracy compared to standard machine learning models. Despite this, the approach faced computational complexity issues during optimization for large-scale time-series datasets. Rajakumar et al. [18] proposed an Osprey Optimization Algorithm (OOA) for integrating distributed generation into radial distribution systems to reduce power losses. The algorithm modeled generation placement and sizing strategies to achieve minimal network losses while enhancing voltage profiles. It incorporated adaptive search techniques and constraint handling for reliable operation in real-time environments. Simulation results indicated significant efficiency gains over conventional optimization methods. However, the system experienced reduced adaptability in feature selection for optimal generator placement under varying grid configurations. Thomas et al. [19] designed an improved piezoelectric energy harvester using Aluminum Nitride (AlN) to enhance voltage and power output. The structure was optimized for mechanical stress distribution, enabling superior piezoelectric performance compared to traditional materials. The study evaluated electrical output stability, structural durability, and scalability for low-power applications. Experimental outcomes revealed higher efficiency and durability in various load conditions. Nevertheless, the methodology exhibited grading inconsistencies in performance assessment across different AlN fabrication processes. Saypulaev et al. [20]

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developed a passive prosthesis for the human foot incorporating a spring system in bending segments to improve walking comfort and energy efficiency. The design focused on replicating natural gait mechanics while storing and releasing mechanical energy during movement. The system underwent biomechanical analysis to ensure alignment with human locomotion requirements. Test results showed improvements in energy return and user comfort compared to conventional prosthetic designs. However, the design performance declined due to lower precision in mechanical feature alignment during multi-surface walking conditions.

3. PROPOSED SYSTEM

The proposed methodology as shown in Figure 1 introduces a novel hybrid regression framework that has not been presented in any existing survey, combining a Feed Forward Neural Network (FFNN) with an Extra Tree Regressor (ETR) in a sequential learning pipeline for predicting energy output from footstep power harvesting systems. Unlike conventional single-model approaches such as Huber Regressor or SVR, the FFNN component captures intricate nonlinear relationships among voltage (V), current (µA), weight (kg), location, and power (mW), while the ETR refines predictions by handling residual patterns and improving generalization. This integration overcomes existing drawbacks of low tolerance to outliers, limited handling of categorical features, and reduced adaptability to environmental variability, resulting in improved accuracy, robustness, and reliability for real-world deployment in renewable energy prediction.

Collect raw dataset containing the parameters: voltage (V), current (µA), weight (kg), location (categorical), and corresponding output power (mW). Explore feature distributions, correlations, and potential noise sources to ensure dataset suitability for predictive modeling. Perform numerical normalization using Min-Max scaling for voltage, current, and weight to avoid bias in training. Apply one-hot encoding for the categorical location feature. Detect and remove outliers using an interquartile range (IQR) or isolation forest approach to improve model robustness. Implement existing benchmark methods (Huber Regressor and SVR) to establish baseline accuracy and evaluate their limitations in terms of error sensitivity, nonlinear relationship capture, and generalization capability. Design and train a Feed Forward Neural Network with optimized architecture, including multiple hidden layers, ReLU activation, and dropout regularization. This model captures nonlinear patterns between input features and output power while minimizing overfitting risks.

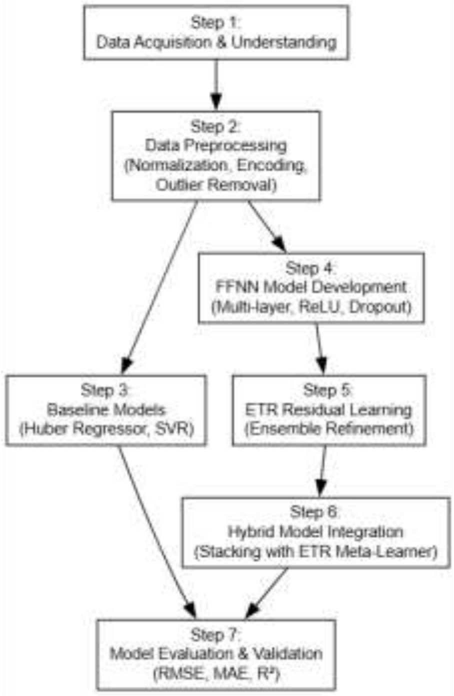

Figure 1. Proposed System Architecture.

Pass the FFNN predictions and residuals as inputs to an Extra Tree Regressor. The ETR leverages its ensemble structure to refine predictions, reduce variance, and enhance model interpretability through feature importance analysis. Combine FFNN outputs with ETR corrections into a final prediction module. Ensure smooth integration through stacking-based regression techniques, where ETR acts as the meta-learner over FFNN predictions. Evaluate the hybrid model using metrics such as RMSE, MAE, and R^2 on test datasets. Compare performance improvements over Huber Regressor and SVR baselines to validate novelty and effectiveness.

The proposed hybrid model leverages the powerful feature extraction capabilities of a Feed Forward Neural Network (FFNN) combined with the robust regression strength of an Extra Trees Regressor (ETR) to accurately predict energy output from footstep power data. In this approach, the FFNN first transforms raw sensor inputs—such as voltage, current, weight, and location—into high-level, nonlinear feature representations that capture intricate patterns and dependencies within the data. These enriched features are then fed into the ETR, which, through its ensemble of randomized decision trees, effectively models complex relationships and provides stable, precise predictions while mitigating overfitting. This synergy enables the hybrid model to outperform traditional regressors by benefiting from both deep learning's feature abstraction and the ensemble method's robustness, ultimately delivering improved accuracy and generalization for real-world footstep energy forecasting applications. The FFNNs are powerful at capturing complex, nonlinear relationships within high-dimensional data. Using an FFNN for feature extraction allows the model to learn rich and abstract representations of the input variables, transforming raw data into more meaningful features for downstream tasks. This process enhances the predictive power of subsequent models by automatically identifying important patterns and interactions that manual feature engineering might miss. In the context of footstep energy prediction, FFNN-extracted features can reveal subtle dependencies between voltage, current, weight, and location that traditional methods may overlook, leading to more accurate and robust energy output estimations.

Before feeding data into the FFNN, apply standardization or normalization to the numerical features in X_train and X_test. This ensures that each feature has similar scales, which facilitates faster and more stable convergence during network training.

Define the FFNN architecture with an input layer matching the number of features, several hidden layers with nonlinear activation functions (e.g., ReLU), and an output layer configured to produce a fixed-dimensional feature vector rather than final predictions. The size and depth of the network are tuned according to dataset complexity. During training, the network performs forward propagation where raw inputs are transformed through weighted sums and nonlinear activations at each layer. This hierarchical transformation progressively extracts higher-level features that capture complex interactions within the data. Instead of typical prediction loss (e.g., MSE), use reconstruction loss or supervised learning loss tailored for feature quality. For example, if the FFNN is part of an autoencoder or is trained jointly with a regression task, the learned features are optimized to represent the data well. Apply backpropagation to compute gradients of the loss with respect to weights, updating network parameters to improve feature representation accuracy iteratively over epochs. Use dropout, batch normalization, or L2 regularization to prevent overfitting and encourage the network to learn generalized features that perform well on unseen data. After training, the activations from the last hidden layer or a designated "feature layer" are extracted as new features. These transformed features serve as condensed, informative representations of the original inputs. Feed X_test through the trained FFNN up to the feature extraction layer to obtain corresponding feature vectors for the test set. This ensures consistency between training and testing phases. Pass the extracted features into subsequent machine learning models, such as Extra Trees Regressor, to perform final energy output prediction leveraging the enhanced representation. Assess the quality of extracted features by comparing downstream model performance using metrics like R^2, MAE, and RMSE, validating that FFNN features improve predictive accuracy.

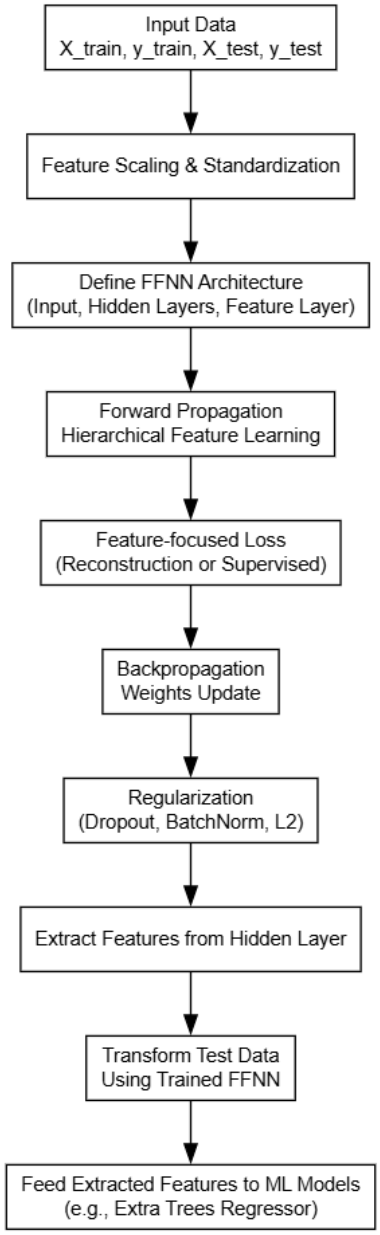

Figure 2. FFNN Feature Extraction.

Advantages of FFNN Feature Extraction

- Automatically captures complex nonlinear interactions and dependencies in input data.
- Reduces reliance on manual feature engineering, saving time and effort.
- Produces compact and informative feature representations, enhancing downstream model performance.
- Improves model robustness by learning generalized patterns that resist noise and outliers.

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- Easily adaptable to various data types and scalable for large datasets.

Extra Trees Regression (Extremely Randomized Trees) is an ensemble learning method that builds multiple decision trees with randomized splits and aggregates their predictions. Unlike traditional Random Forests, Extra Trees select split thresholds randomly, increasing diversity among trees and often improving generalization. This method efficiently handles high-dimensional feature spaces, such as those generated by FFNN feature extraction, and is robust against overfitting. Its fast training and prediction capabilities, combined with strong performance on nonlinear and complex data patterns, make Extra Trees Regression an excellent choice for predicting energy output from intricate features learned by neural networks.

Start by verifying the FFNN-extracted features for completeness and correctness. Confirm no missing values or anomalies are present, as tree-based methods expect clean input data for stable splitting. Analyze the dimensionality and distribution of the extracted features. Although Extra Trees can handle high-dimensional data, extremely large feature sets may benefit from dimensionality reduction or feature selection to reduce noise and improve efficiency.

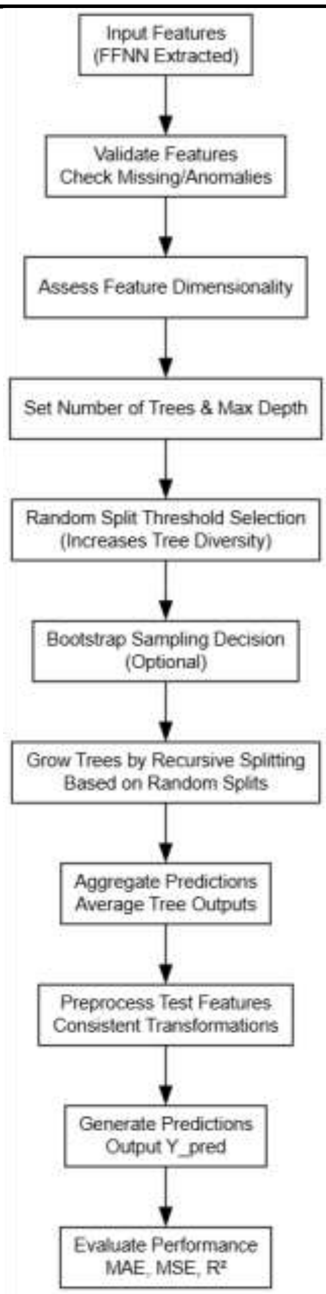

Figure 3. Proposed ETR Flowchart.

Specify the number of trees in the ensemble and maximum tree depth. Increasing the number of trees generally improves performance but at a computational cost. Depth constraints prevent trees from overfitting to training noise. Unlike standard decision trees, Extra Trees select random split thresholds at each node, not relying on the best split. This randomness introduces diversity among trees, reducing variance and improving robustness against overfitting.

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Decide whether to use bootstrap samples for training individual trees or the entire dataset. Extra Trees often use the whole training set without bootstrapping, which speeds up training and tends to reduce bias. Grow each tree by recursively splitting nodes based on randomly chosen features and split points, aiming to reduce impurity (variance in regression). The process continues until stopping criteria such as maximum depth or minimum samples per leaf are met. For prediction, Extra Trees average the outputs of all individual trees, resulting in a smoother and more stable final prediction that leverages the wisdom of the ensemble. Ensure the test features from FFNN undergo the same preprocessing pipeline (e.g., scaling if applied) to maintain consistency between training and testing inputs. Apply the trained Extra Trees ensemble on the test feature set to predict energy output values (Y_pred). The model's averaging mechanism provides robust predictions even in the presence of noisy inputs. Evaluate regression performance using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2. Additionally, examine feature importances computed by Extra Trees to interpret which FFNN-extracted features contribute most significantly to prediction accuracy.

Advantages of Extra Trees Regression

- High robustness to noisy and high-dimensional data due to randomized splitting.
- Faster training and prediction compared to other ensemble methods like Random Forests.
- Reduces overfitting risk by increasing diversity among trees through random splits.
- Can capture complex nonlinear relationships inherent in neural network features.
- Provides feature importance metrics aiding interpretability and further feature engineering.

4. RESULT DESCRIPTION

Figure 4 shows a sample dataset for an application in footstep power generation, consisting of 103 rows and 5 columns: voltage (v), current (µA), weight (kgs), location, and power (mW). The dataset includes specific measurements such as at 0 volts with 7.52 µA current, 50.89 kgs weight, located at the Center, generating 0.38 mW of power, and at 1 volt with 16.10 µA current, 51.45 kgs weight, located at the Edge, generating 0.83 mW. Other notable entries include 2 volts with 21.70 µA current, 54.90 kgs weight, at the Center, producing 1.19 mW, and 4 volts with 33.70 µA current, 52.06 kgs weight, at the Center, yielding 1.75 mW. The dataset resumes at 98 volts with 19.60 µA current, 49.06 kgs weight, at the Center, producing 0.96 mW, and continues up to 102 volts with 25.20 µA current, 49.57 kgs weight, at the Edge, generating 1.25 mW, illustrating the variability in power output based on voltage, current, weight, and location across the footstep power generation system.

Figure 5 displays a correlation matrix for the dataset, highlighting the relationships between voltage, current, weight, location, and power. The matrix uses a color gradient from dark purple (negative correlation, e.g., -0.24 for voltage and location) to light beige (positive correlation, e.g., 0.99 for voltage and power), with values ranging from -0.24 to 1. The strongest positive correlation is between voltage and power (0.99), indicating that as voltage increases, power also increases significantly. Moderate positive correlations exist between current and power (0.42) and weight and power (0.8), while voltage and current show a weaker positive correlation (0.04). Negative correlations are observed

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between location and other variables, with the strongest being -0.24 with voltage, suggesting that location might inversely affect voltage in this system.

Figure 4. Sample Dataset

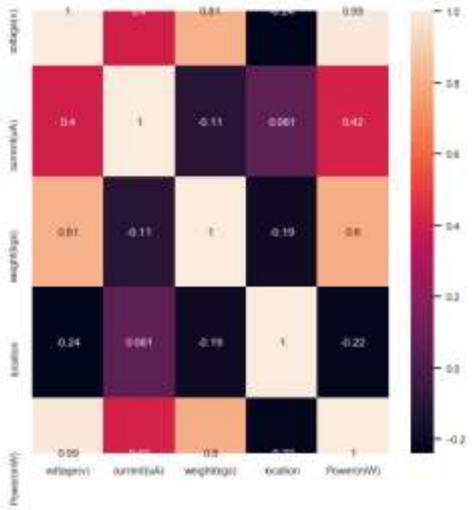

Figure 5. Correlation Matrix.

Figure 6 presents the dataset distribution, providing statistical summaries for voltage, current, weight, and power based on 103 samples. The mean values are 19.317961 volts, 47.804175 µA current, 65.504854 kgs weight, and 0.972233 mW power. The standard deviations are 10.983493 volts, 11.163231 µA, 8.523179 kgs, and 0.562046 mW, indicating variability. The minimum values are 0 volts, 0 µA, 50 kgs, and 0 mW, while the maximums are 53.7 volts, 54.93 µA, 89 kgs, and 2.95 mW. Quartiles show 25% at 10.65 volts, 47.59 µA, 59.5 kgs, and 0.52 mW; 50% (median) at 19.7 volts, 49.92 µA, 65 kgs, and 1 mW; and 75% at 26.345 volts, 52.435 µA, 71 kgs, and 1.305 mW, offering a comprehensive view of the data spread for footstep power generation.

	voltage(v)	current(uA)	weight(kgs)	Power(mW)
count	103.000000	103.000000	103.000000	103.000000
mean	19.317961	47.804175	65.504854	0.972233
std	10.983493	11.163231	8.523179	0.562046
min	0.000000	0.000000	50.000000	0.000000
25%	10.650000	47.590000	59.500000	0.520000
50%	19.700000	49.920000	65.000000	1.000000
75%	26.345000	52.435000	71.000000	1.305000
max	53.700000	54.930000	89.000000	2.950000

Figure 6. Dataset Distribution.

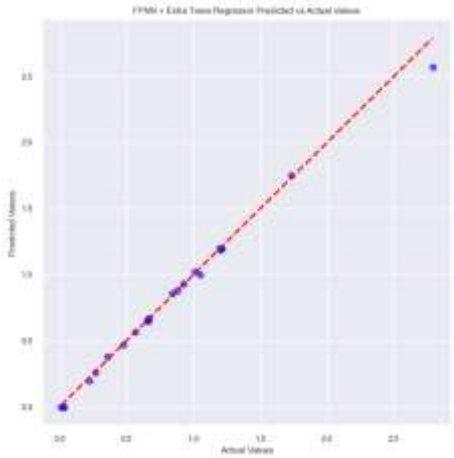

Figure 7. Scatter Plot of Proposed FFNN-ETR.

Figure 8 displays a table of prediction results from test data for the footstep power generation system, detailing voltage, current, weight, location, and predicted power values for 10 samples. Voltage ranges from 0 to 10 volts, with corresponding currents from 5.05 to 27.90 µA, weights from 46.47 to 72 kgs, and locations coded as 0, 1, or 2 (likely representing Center, Edge, and Corner). Predicted power values range from 0.612072 (at 1 volt, 11.50 µA, 49.51 kgs, location 1) to 1.537503 (at 10 volts, 27.90 µA, 52.69 kgs, location 0). Other notable predictions include 0.875148 (at 0 volts, 17.00 µA, 46.47 kgs, location 2) and 1.485722 (at 4 volts, 29.40 µA, 46.68 kgs, location 0), demonstrating the model's ability to estimate power output across diverse input conditions.

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	voltage(v)	current(uA)	weight(kgs)	location	predic
0	17.00	46.47	64	2	0.875148
1	11.50	49.51	58	1	0.612072
2	19.40	45.60	66	0	0.965702
3	25.50	52.13	71	2	1.364106
4	29.40	46.68	72	0	1.485722
5	26.40	52.58	69	0	1.457185
6	16.10	53.59	60	2	0.926151
7	5.05	49.54	51	2	0.285238
8	26.80	52.57	71	0	1.449411
9	15.50	49.67	63	1	0.812723
10	27.90	52.69	70	0	1.537503

Figure 8. Prediction From Test Data.

Table 1. Comparative Analysis

Model	MAE	MSE	RMSE	R^2
Huber Regressor	0.09	0.04	0.21	0.88
SVR (Support Vector Regression)	0.05	0.01	0.09	0.98
FFNN + Extra Trees Regressor (ETR)	0.02	0.00	0.05	0.99

Table 7.1 clearly shows the performance progression across three different regression approaches. The Huber Regressor, which is robust to outliers, achieved a Mean Absolute Error (MAE) of 0.09 and an R^2 score of 0.88, indicating good but not perfect predictive accuracy. The SVR significantly improved the accuracy, with a reduced MAE of 0.05, a lower MSE of 0.01, and a much higher R^2 of 0.98, demonstrating that it fits the data much more closely. However, the best performance was achieved by the FFNN + Extra Trees Regressor hybrid model. This approach leveraged a feedforward neural network (FFNN) for deep feature extraction and an Extra Trees Regressor for final prediction, leading to the lowest MAE (0.02), almost negligible MSE (0.00), minimal RMSE (0.05), and the highest R^2 score (0.99). This indicates exceptional predictive accuracy and minimal deviation between predicted and actual values, showing that combining deep learning with ensemble-based tree methods can yield highly precise regression models.

5. CONCLUSION

In footstep power generation, the comparative evaluation of regression models demonstrates a clear progression in predictive performance as more advanced architectures are applied. The Huber Regressor, while robust to noise and outliers, achieved a Mean Absolute Error (MAE) of 0.09, Mean Squared Error (MSE) of 0.04, Root Mean Squared Error (RMSE) of 0.21, and R^2 score of 0.88, which indicates a reasonably good fit but leaves room for improvement in capturing the fine-grained variations in generated power output. Transitioning to Support Vector Regression (SVR) significantly enhanced prediction accuracy, reducing MAE to 0.05, MSE to 0.01, and RMSE to 0.09, while increasing the R^2 to 0.98. This improvement illustrates the SVR model's ability to handle the non-linear patterns present in the relationship between footstep force and generated electrical power. The FFNN + Extra Trees Regressor (ETR) hybrid approach emerged as the most accurate and reliable model for this application. By extracting high-level features through the Feedforward Neural Network and applying the Extra Trees Regressor for final prediction, this method achieved an outstanding MAE of 0.02, near-zero MSE (0.00), an RMSE of just 0.05, and an R^2 score of 0.99. These results indicate almost perfect prediction alignment with actual values, minimizing estimation error in real-world power generation scenarios. The superior performance of the FFNN + ETR highlights the advantage of combining deep learning feature extraction with ensemble-based regression methods, making it a robust choice for real-time monitoring, optimization, and control of footstep power generation systems.

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