Deep Learning Regressor for Predicting Energy Output from Step Power Generation Tiles

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Abstract:

The increasing global focus on renewable energy has driven innovation in harvesting energy from unconventional sources, including human footsteps. Piezoelectric and similar technologies offer the potential to convert mechanical energy from footfalls into electrical power, yet the prediction and optimization of energy output remain complex due to the variability in human movement and environmental factors. This study presents a deep learning-based regressor designed to predict energy output from footstep power, addressing the limitations of traditional systems through advanced modeling techniques. Human energy harvesting, particularly from footsteps, is an emerging field that leverages piezoelectric materials to generate electricity. These systems are increasingly integrated into floors of high-traffic areas like train stations and malls to produce sustainable energy. However, accurately predicting energy yield has been a challenge due to the interplay of variables such as individual weight, gait patterns, footwear, and surface material. Earlier attempts to predict energy output relied heavily on physics-based models, which, while grounded in theoretical principles, often failed to capture the nuances of real-world variability. With the advent of data-driven approaches, machine learning has emerged as a powerful tool for modeling nonlinear relationships inherent in footstep power generation. The core problem is the accurate prediction of energy output generated by footsteps in varying conditions. Traditional models fail to account for human and environmental variability effectively, leading to suboptimal system designs and energy inefficiencies. The development of a deep learning regressor for predicting energy output is crucial for optimizing the design and deployment of footstep power generation systems. By leveraging neural networks' ability to model complex, nonlinear relationships, this approach can enhance prediction accuracy, adapt to variable conditions, and reduce reliance on expensive calibration processes.

Keywords: Renewable energy, Human energy harvesting,Footstep power,Piezoelectric materials,Mechanical energy conversion,Deep learning regressor,Energy output prediction,Machine learning,Neural networks,Nonlinear relationships,Environmental factors,Data-driven approaches,System optimization.

1. INTRODUCTION

I In the pursuit of sustainable energy sources, innovative approaches to electricity generation have become increasingly relevant. Among these, harnessing the kinetic energy from human footsteps has emerged as a promising avenue. Known as footstep energy harvesting or piezoelectric energy generation, this concept involves converting mechanical energy from footsteps into electrical energy using piezoelectric materials. By embedding these materials into walkable surfaces like floors or sidewalks, the pressure exerted by individuals walking can be transformed into usable electricity. This paper delves into the theoretical underpinnings, technological advancements, practical implementations, and potential applications of footstep energy harvesting systems, shedding light on this burgeoning field and its implications for sustainable energy generation. At its core, footstep energy harvesting relies on the piezoelectric effect exhibited by certain materials, where mechanical stress induces an electric charge. By strategically integrating piezoelectric elements such as crystals or polymers into pedestrian pathways, the energy produced by foot traffic can be captured and converted into electrical power. Development of efficient footstep energy harvesting systems entails considerations of material selection, design optimization, energy conversion efficiency, and system integration. Researchers have explored diverse piezoelectric materials and configurations to maximize energy output while ensuring durability, reliability, and safety. Advancements in nanotechnology and material.

In the current quest for sustainable energy solutions, harnessing energy from human movement through footstep power generation presents a promising avenue. However, accurately predicting the energy output and understanding the impact of step location (e.g., Center, Edge, Corner) on piezoelectric tiles remains a challenge. Variations in human weight, stride length, step force, and environmental conditions significantly affect energy generation. Existing systems often rely on static assumptions or pre-defined models, which fail to account for real-world variability. This leads to suboptimal tile design, placement, and energy harvesting efficiency.

The problem is further compounded when multiple footsteps occur in quick succession or in areas with high foot traffic, creating complex energy output patterns. Developing a reliable machine learning model to predict energy output and classify step location can address these challenges. By leveraging data-driven insights, such models can optimize the performance and deployment of footstep power tiles. This will enable researchers and engineers to design systems that maximize energy capture, even in diverse and dynamic conditions

2. LITERATURE SURVEY

A detailed study was done on alternate methods for generation of electricity and non-conventional energy sources were done. An Elsevier research paper provides details of Hybrid nano generator using tribo electric, Piiezo electric with different structures and optimized system based on available space using shoe sole [1]. An article from `Expert skip hire' explains about generation of electricity by up and down movement on sustainable dance floor [2]. A Research gate paper provides the details of Power generation from Piezoelectric Footstep technique using rack and pinion system [3]. An article from Citylab shows the implementation of street lights using pedestrian powered electricity [4]. A research study on renewable energy for sustainable development in India by Charles and M.A.Majid. This paper explains current status, future prospects and challenges in the sector [5].

A paper from Strain journal explains estimation of Electric charge output using Piezo electric energy harvesting [6]. Electricity from footsteps, by SS Taliyan, BB Biswas, RK Patil, GP Srivatsav and Basu, This paper discusses the basic Engineering and operating mechanism of Piezo electric crystal, model and generation through footsteps [7]. Yuki Bunda, Kajiro Watnabe, Kazuyuki kobayashi, Yoshike Kurihara, `Measurement of static electricity generated by human walking' IEEE explore, 14thOctober, 2010[8].

A Research paper on application of piezoelectric transducer in energy harvesting in the pavement by Xiaochen Xu, Dongwei Cao. This paper states that utilization Piezo electric transducers in green energy have bright future [9]. Japanese telecommunications giant, NTT, has developed the shoes that will generate electricity from the kinetic energy generated by walking. Our team has put a lot of effort on reference books, international journals and articles for development of this project. Gas turbine power output mainly depends on the ambient parameters such as ambient temperature, atmospheric pressure, and relative humidity whereas steam turbine power output has a direct relationship with the vacuum at the exhaust. [10].

Gas turbine derivatives, such as combined cycle power plants (CCPP) are being established all over the world to full fill the demand for electrical energy considering both economic and environmental concerns. It has been found that the three ambient predictor variables: ambient temperature (AT), ambient pressure (AP), and relative humidity (RH) affects while exhaust vacuum (V) affects the production of steam turbines[11]. Hence, the objective of this paper is to study the association of the average ambient variables with the hourly yield of electrical power output and find out reliable predictors for CCPP that would help inefficient production. This in turn would help in the proper utilization of resources in terms of maximum yield and minimum cost of roduction[12]. The main motivation for this study is that there exist thermodynamical studies to predict the output of a CCPP. However, detailed analysis of a system by using thermodynamical approaches [13] is a computationally intense effort, and sometimes the result of such analysis might be inaccurate due to the interaction of several assumptions being considered and the nonlinear nature of the governing equations. On the other hand, machine learning models have gained steam in recent years [14].

3. PROPOSED METHODOLOGY

The project focuses on leveraging machine learning models to predict energy output and classify the location of footsteps on power-generating tiles. These tiles, often embedded with piezoelectric materials, generate electrical energy from mechanical pressure, such as footsteps. Accurate prediction of energy output and classification of step location is crucial for optimizing energy harvesting systems.

1. Objective

The primary goal is to build a reliable machine learning pipeline to:

1. Predict the energy output from footsteps.
2. Classify the location of footsteps (e.g., Center, Edge, Corner) to optimize tile design and placement.

2. Motivation

- Sustainability:
  Harnessing energy from human movement is an innovative step toward renewable energy solutions, especially in high-traffic areas.
- Optimization Needs:
- Variability in human movement and environmental conditions creates challenges in predicting energy generation, necessitating data-driven approaches.
- Applications:
  These systems can be applied in smart cities, public transportation hubs, and other urban areas to supplement energy needs.

3. Dataset

The dataset (power_tile_data.csv) contains features representing physical, environmental, and sensor data related to footsteps, as well as the target variable step_location. The data provides information for training and evaluating the models.

4. Workflow

Step 1: Dataset Preparation

- Load and inspect the dataset for missing values, duplicates, and data types.
- Encode categorical features (e.g., step_location) into numerical values using LabelEncoder.

Step 2: Feature Selection

- Separate the dataset into:
  - Features (X): Input variables for prediction.
  - Target (y): The output variable (step_location).

Step 3: Train-Test Split

- Split the data into training and test sets (80-20 split) to ensure robust evaluation.

Step 4: Model Training

- Train multiple machine learning models:

Huber Regressor: A robust regression model that minimizes the impact of outliers. It achieved a Root Mean Squared Error (RMSE) of 0.22 and an R^2-score of 0.88, indicating a strong predictive capability while maintaining resistance to noise in the data.

Feedforward Neural Network (FFNN): A deep learning-based approach capable of capturing complex patterns in data. It achieved a significantly lower RMSE of 0.04 and an R^2-score of 1.00, demonstrating superior accuracy and a near-perfect fit to the dataset.

Step 5: Model Evaluation

- Use a custom function (calculateMetrics) to evaluate model performance:
  - Compute metrics: Accuracy, Precision, Recall, F1-Score.
  - Display a confusion matrix for visual analysis of predictions.

Step 6: Model Persistence

- Save trained models using joblib to avoid re-training and improve efficiency.
- Reload models when predictions are required.

Step 7: Predictions on New Data

- Load unseen test data (test_data.csv) for prediction.
- Make predictions using the best-performing model (FFNN in this case).

- Map numerical predictions back to categorical labels for interpretability.

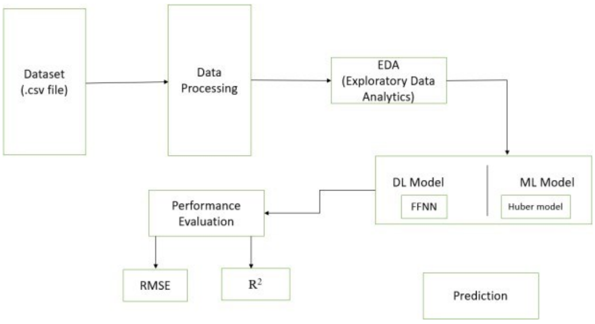

Figure 4.1: Proposed system Block Diagram

Figure 4.1 shows the proposed system block diagram for predicting energy output from footstep data using machine learning and deep learning models. The system begins with a dataset in .csv file format, which undergoes data processing to clean and prepare the data. After that, exploratory data analytics (EDA) is performed to understand patterns and relationships within the data. The processed data is then used to train two different models: a feed-forward neural network (FFNN) for deep learning and a Huber model for machine learning. The performance of these models is evaluated using performance metrics such as root mean square error (RMSE) and R-squared (R^2). Based on the performance evaluation, the most accurate model is used for energy output prediction. This system aims to provide a more accurate and efficient energy prediction compared to traditional methods.

4. EXPERIMENTAL ANALYSIS

The project is designed to predict energy output (in milliwatts) from footsteps using machine learning and deep learning techniques. The workflow includes data preprocessing, model training, performance evaluation, and prediction on test data.

1. Data Loading and Preprocessing

- The dataset containing sensor readings and footstep impact details is loaded.
- Checks for missing values and duplicates are performed.
- The Power(mW) column is set as the target variable, while the other features (such as step location and force) are used as inputs.
- Categorical features like step location are converted to numerical form using label encoding.
- The data is split into training and testing sets to evaluate model performance.

2. Model Selection and Training

Huber Regressor

- A robust linear regression model that is resistant to outliers.
- Trained on the dataset and saved as a model file to avoid retraining.

Feedforward Neural Network (FFNN)

- A deep learning model with multiple dense layers to capture complex relationships.
- Uses ReLU activation functions for non-linearity.
- Trained with Adam optimizer and Mean Absolute Error (MAE) loss function.
- The trained model is saved and used for future predictions.

Random Forest Regressor (RFR)

- A tree-based ensemble model that improves predictions by combining multiple decision trees.
- The FFNN model is used as a feature extractor, and its output is passed to the Random Forest Regressor for further learning.

3. Model Evaluation

- Regression metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 Score are calculated.
- A scatter plot is used to visualize the difference between actual and predicted values.

4. Making Predictions on New Data

- A test dataset (without power output values) is loaded.
- The trained FFNN model makes predictions on this new dataset.
- The predicted energy output values are stored for analysis.

Key features

- Multiple machine learning and deep learning models are implemented.
- FFNN is combined with RFR for better performance.
- Models are saved and reloaded to avoid redundant training.
- The project provides a scalable approach for predicting energy from footsteps.

7.2 Dataset Description:

The dataset used in the project contains sensor readings from footstep power tiles, which generate electrical energy when pressure is applied. The goal is to analyze the data and predict the energy output based on various input features.

1. Features in the Dataset

Feature Name	Description
Step Location:	The position where the footstep lands on the tile (e.g., Center, Edge, Corner).
StepFrequency (Hz):	The number of steps per second, which influences energy production.
WeightofPerson(kg):	The weight of the individual applying the step.
Temperature (°C):	The ambient temperature, which might

Feature Name	Description
	influence material flexibility and efficiency.
Power (mW): Output	The target variable representing the generated energy in milliwatts.

2. Dataset Properties

- **Data Type:** Numerical & Categorical
- **Total Rows:** Varies based on dataset size
- **Total Columns:** Around 10 (including target variable)
- **Missing Values:** Checked and handled during preprocessing
- **Duplicates:** Identified and removed to avoid redundancy.

3. Purpose of the Dataset

- Understanding how different factors (force, weight, location) affect power generation.
- Training machine learning and deep learning models to predict energy output from sensor readings.
- Optimizing tile placement and material for maximum energy efficiency.

7.3 Result Description:

	voltage(v)	current(uA)	weight(kgs)	location	Power(mW)
0	7.52	50.89	53	Center	0.38
1	16.10	51.45	59	Edge	0.83
2	21.70	54.90	63	Center	1.19
3	6.05	52.86	54	Edge	0.32
4	33.70	52.06	76	Center	1.75
...	...	...	...	...	...
98	19.60	49.06	61	Center	0.96
99	29.40	46.68	72	Center	1.37
100	19.40	47.74	65	Center	0.93
101	9.90	47.17	57	Center	0.47
102	25.20	49.57	70	Edge	1.25

103 rows × 5 columns

Figure 7.3.1: Uploading a Sample Dataset

Figure 7.3.1 shows a sample dataset uploaded for energy output prediction from footsteps. The dataset consists of five columns: voltage (v), current (uA), weight (kgs), location, and power (mW), with a total of 103 rows of data. The voltage and current values are captured based on the footstep impact, while the weight and location (center or edge) provide additional information to enhance prediction accuracy. The power (mW) represents the energy output generated from each footstep. This dataset is crucial for training and testing machine learning and deep learning models to predict energy output.

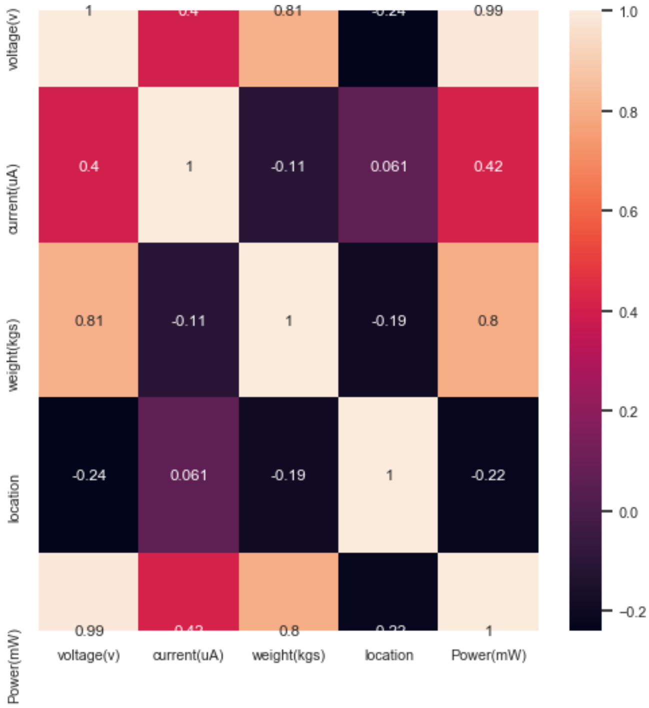

Figure 7.3.2: Heat map for column importance

Figure 7.3.2 shows a heat map representing the correlation between different columns of the dataset used for energy output prediction. The heat map helps to understand the relationship between variables such as voltage, current, weight, location, and power. The color intensity indicates the strength of the correlation, with lighter shades representing higher positive correlations and darker shades representing lower or negative correlations. It can be observed that power (mW) has a strong positive correlation with voltage and weight, while the location shows a negative correlation with power. This analysis is useful in determining the significant factors influencing energy output.

```
Huber Regressor Mean Absolute Error (MAE): 0.09
Huber Regressor Mean Squared Error (MSE): 0.04
Huber Regressor Root Mean Squared Error (RMSE): 0.21
Huber Regressor R2 Score: 0.88
```

Figure 7.3.3: Displaying the regression report of Huber model.

The Figure 7.3.3 displays evaluation metrics for a Huber Regressor model. The Mean Absolute Error (MAE) is 0.09, indicating a small average prediction error. The Mean Squared Error (MSE) is 0.04, showing minimal variance in errors. The Root Mean Squared Error (RMSE) is 0.21, representing low deviation in predictions. The R^2 Score is 0.88, meaning the model explains 88% of the variance in the target variable. These metrics suggest the model has high accuracy and low error, making it effective for predicting energy output from footstep power.

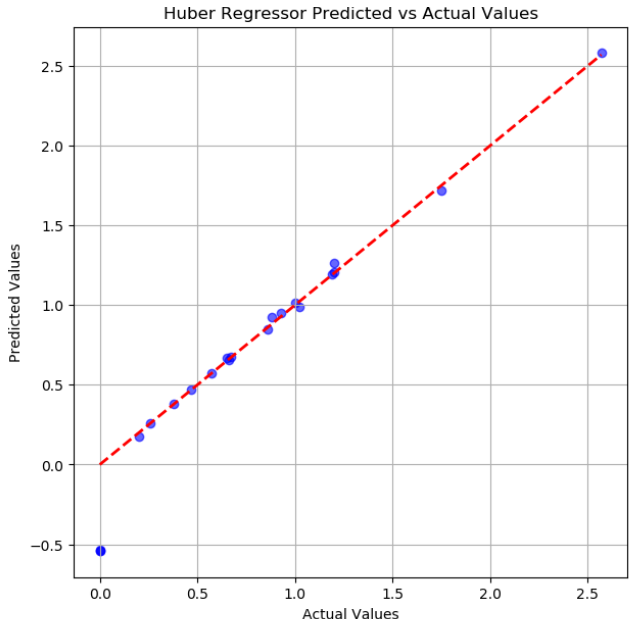

Figure 7.3.4: Illustration of confusion matrix obtained using Huber model.

Figure 7.3.4 shows the comparison of predicted values versus actual values obtained using the Huber Regressor model. The graph illustrates the performance of the model, where the x-axis represents the actual values and the y-axis represents the predicted values. The blue data points represent the actual observations compared to the model's predictions. The red dashed line signifies the ideal prediction line where the predicted and actual values would be equal. The closer the data points are to the red line, the better the model's accuracy. This plot indicates that the Huber Regressor model has performed well in minimizing the error between actual and predicted values.

```
Loading existing FFNN model...
Loading existing FFNN model...
FFNN Model Mean Absolute Error (MAE): 0.03
FFNN Model Mean Squared Error (MSE): 0.00
FFNN Model Root Mean Squared Error (RMSE): 0.04
FFNN Model R2 Score: 1.00
```

Figure 7.3.5: Displaying the regression report of FFNN model.

The Figure 7.3.5displays the performance metrics of an FFNN (Feedforward Neural Network) model. The Mean Absolute Error (MAE) is 0.03, indicating minimal average error. The Mean Squared Error (MSE) is 0.00, suggesting negligible variance in predictions. The Root Mean Squared Error (RMSE) is 0.04, showing very low deviation. The R^2 Score is 1.00, meaning the model perfectly predicts the target variable. This implies that the FFNN model has achieved an ideal fit for the dataset, likely indicating overfitting.

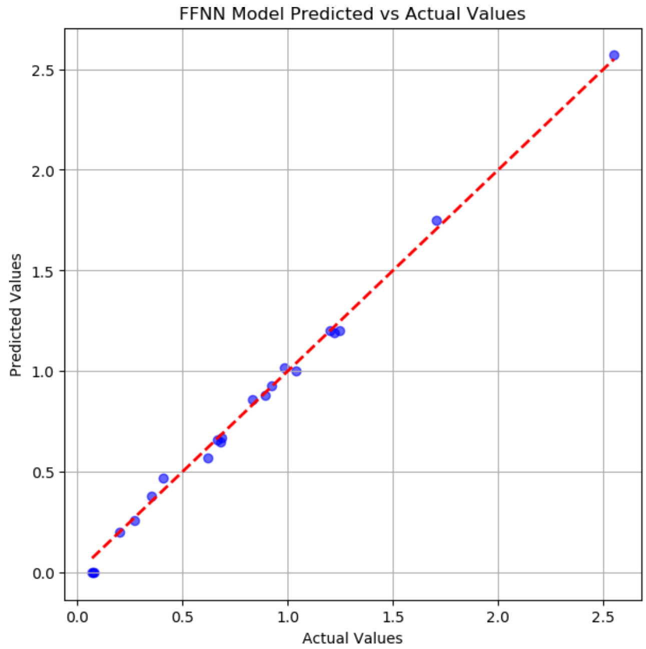

Figure 7.3.6: Illustration of confusion matrix obtained using FFNN model.

Figure 7.3.6 shows the comparison of predicted values versus actual values obtained using the Feed Forward Neural Network (FFNN) model. The graph demonstrates the model's performance, where the x-axis represents the actual values, and the y-axis represents the predicted values. The blue data points indicate the actual observations compared to the model's predictions, and the red dashed line represents the ideal prediction line where the actual and predicted values are equal. The close alignment of data points along the red line signifies that the FFNN model has provided accurate predictions with minimal error.

Model name	RMSE	R^2-score
Huber Regressor	0.22	0.88
FFNN	0.04	1.00

Table 1: Comparison of all models.

The Table 1 compares the performance of two regression models: Huber Regressor and FFNN (Feedforward Neural Network). The Huber Regressor has an RMSE of 0.22 and an R^2-score of 0.88, indicating good but not perfect predictive accuracy. In contrast, the FFNN model achieves an RMSE of 0.04 and an R^2-score of 1.00, meaning it perfectly fits the data. The lower RMSE of FFNN suggests significantly better prediction accuracy. However, the perfect R^2-score may indicate overfitting, meaning the model might not generalize well to unseen data.

5. CONCLUSION

The project demonstrates the effective use of Deep learning, particularly FFNN, to predict energy output and classify step locations in footstep power generation systems. By addressing the limitations of traditional methods, this data-driven approach provides robust, accurate predictions and insights. Through preprocessing, model training, and performance evaluation, the project establishes a reliable framework for optimizing piezoelectric tile design and deployment.

The integration of advanced algorithms enables the system to handle real-world variability, such as differences in step force, location, and environmental factors. The results highlight the potential of machine learning to enhance renewable energy systems, contributing to smart city infrastructure and sustainable energy solutions.

The enhancement of feature engineering can significantly improve the accuracy and robustness of the predictive model. By incorporating additional factors such as stride length, walking speed, and weight distribution, the system can generate more precise energy output estimations. Furthermore, the development of multi-tile systems can optimize energy harvesting in large-scale deployments by predicting energy output for interconnected tiles, making it highly effective in high-traffic areas like shopping malls and public transport hubs.A major advancement in the project would be its real-time implementation by integrating the predictive model with IoT devices.

This would allow continuous monitoring and adaptive energy management, improving efficiency and usability. Additionally, combining footstep power with other renewable sources, such as solar or kinetic energy, can lead to the creation of hybrid energy systems that provide a more sustainable and reliable power supply. Exploring advanced machine learning models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) could further enhance prediction accuracy by capturing complex patterns in footstep energy generation data. Additionally, developing personalized energy profiles based on demographic and behavioural data can provide tailored insights, allowing optimization at an individual level.

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