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AN AI-DRIVEN MACHINE LEARNING FRAMEWORK FOR SUSTAINABLE DEVELOPMENT: ENERGY EFFICIENCY, CLIMATE MODELLING, AND INTELLIGENT WASTE CLASSIFICATION

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Abstract

In this research paper, the design, implementation, and evaluation of a all-encompassing machine learning system to support sustainable development is conducted, covering three interrelated areas, including energy efficiency forecasting at the household level, downscaling climate change and detecting extreme events through deep learning, and automated waste classification with convolutional neural networks. It has been applied to real-world data using Python and TensorFlow, Scikit-learn, and PyTorch, such as the UCI Household Power Consumption dataset (2,049,280 samples), ERA5 reanalysis climate data, and the joint TrashNet/TACO waste image dataset (4,000+ labeled images). An forecaster of standardised hourly energy yields RMSE = 0.0237 (R^2 = 0.9995) with a Random Forest Regressor and a stable sequential learning MSE = 0.385 at 50 training epochs with a network based on an LSTM. A CNN-LSTM hybrid model decreases climate downscaling RMSE by 63.2% compared to bilinear interpolation baselines (R 2 = 0.924). A fine-tuned ResNet-50 is over 90 percent waste classification accuracy (weighted F1 = 0.902) six waste types. Analyses of SHAP and LIME indicate that scientific validity of model outputs are valid, and autoregressive lag features explain more than 42 percent of the importance of energy predictions. The integrated framework specifically responds to SDG 7, SDG 12 and SDG 13 of the UN Sustainable Development Goals, offering a deployable, modular and interpretable AI system to sustainable infrastructure management.

Keywords: *Random Forest, LSTM, CNN, ResNet-50, Energy Forecasting, Climate Downscaling, Waste Classification, SHAP, Sustainable Development Goals, Python, TensorFlow*

1. Introduction

The escalating urgency of global sustainability issues, such as increased energy consumption, rapid climate change and the rising amount of waste, impose a technical rigor, scale, and deployment requirements. Machine learning offers an effective computing model to overcome these issues by transforming high dimensional data streams into actionable predictions, classifications and optimization choices. The original implementation and experimental findings of a Python-based integrated ML framework to achieve three domains of sustainability in line with the United Nations Sustainable Development Goals (SDGs) are reported in this paper. The main research contributions to the study are: (1) a data engineering and feature engineering pipeline with the UCI Household Power Consumption dataset; (2) a comparative study between the Random Forest and LSTM architecture in terms of smart grid demand forecasting; (3) a CNN-LSTM hybrid implementation and validation on the ERA5 climate downscaling; (4) multi-class waste classification with ResNet-50 fine-tuning and The complete reproducibility of all the code, datasets and evaluation results is demonstrated.

2. Datasets and Preprocessing

2.1 UCI Household Power Consumption Dataset

The main energy data set includes 2,049,280 minute-resolved values of a single residential home in France (December 2006-November 2010) including a total of seven sensor channels: Global Active Power (kW), Global Reactive Power (kW), Voltage (V), Global Intensity (A) and three sub-metering channels of kitchen, laundry, and HVACThe raw CSV has approximately 1.25% missing values, which are denoted by the character of '?', which is evenly distributed across all channels indicating periodic sensor failures.

Table 1: Descriptive Statistics of the UCI Household Power Consumption Dataset (After Preprocessing)

Feature	Mean	Std Dev	Min	Max	Missing (%)
Global_active_power (kW)	1.0916	1.0573	0.076	11.122	1.25%
Global_reactive_power (kW)	0.1237	0.1127	0.000	1.390	1.25%
Voltage (V)	240.84	3.240	223.2	254.15	1.25%
Global_intensity (A)	4.628	4.444	0.200	48.40	1.25%
Sub_metering_1 (Wh)	1.122	6.153	0.000	88.00	1.25%
Sub_metering_2 (Wh)	1.299	5.822	0.000	80.00	1.25%
Sub_metering_3 (Wh)	6.458	8.437	0.000	31.00	1.25%

2.2 Data Loading and Initial Preprocessing

Code 1 — Data Loading and Datetime Parsing

```
BEGIN

Import pandas library
Import os library
```

```
Construct file path

Read dataset
    Separator = ';'
    Missing value symbol = '?'

Create datetime string
    Date + Time

Convert datetime string to datetime format

Remove Date column
Remove Time column
Remove temporary datetime string

Set datetime as dataset index

FOR each missing value

    Replace with previous valid value

END FOR

Calculate dataset shape

Calculate minimum date

Calculate maximum date

Verify missing values = 0

Store cleaned dataset

END
```

2.3 Feature Engineering

Code 2 — Time Features and Hourly Resampling

```
BEGIN

Load cleaned time-series dataset

Extract hour from datetime
```

```
Extract day_of_week from datetime
Extract month from datetime
Define aggregation rules
Resample dataset to hourly intervals
FOR lag = 1 TO 3
    Create lag feature from Global_active_power
END FOR
Compute rolling_mean_6h
Compute rolling_std_6h
Remove rows containing NULL values
Count total hourly records
Count total feature columns
Split data chronologically
    Training = 70%
    Validation = 15%
    Test = 15%
Store datasets
END
```

3. Energy Efficiency Forecasting

3.1 Random Forest Regressor Implementation

Random Forest Regressor was chosen as the initial short-term forecasting model because it can model non-linear autoregressive dependencies, is resistant to overfitting, feature importance is built in, and has a fast-training time.All continuous features were normalized using StandardScaler and then trained with no feature leakage since StandardScaler was only trained on training data.

Code 3 — Random Forest Training and Evaluation

```
BEGIN
Import machine learning libraries
Initialize StandardScaler
Select numerical columns
Fit scaler using training data
FOR each dataset
    Standardize numerical features
END FOR
Select predictor features
Remove Global_active_power from inputs
Initialize Random Forest Regressor
    Number of Trees = 50
    Random State = 42
    Parallel Processing = TRUE
Train model using training dataset
Predict target values for test dataset
Compute RMSE
Compute MAE
Compute $R^2$ Score
Display evaluation metrics
Display training time
END
```

3.2 LSTM Sequential Model Implementation

Code 4 — LSTM Architecture and Sequence Generation

```
BEGIN

Import TensorFlow libraries

Define create_sequences function

Set lookback = 24

Select predictor features

Generate training sequences

Generate validation sequences

Initialize Sequential model

Add LSTM layer
   Units = 50
   Activation = ReLU
   Input Shape = (24,14)

Add Dense layer
   Units = 1

Compile model
   Optimizer = Adam(0.001)
   Loss = Mean Squared Error

Configure EarlyStopping
   Patience = 5
   Restore Best Weights = TRUE

FOR epoch = 1 TO 50

   Forward Propagation

   Compute Loss

   Backpropagation Through Time

   Update Weights

   Calculate Validation Loss
```

```
END FOR
Store Training History
Display Model Summary
END
```

Table 2: Model Performance Comparison on Energy Efficiency Forecasting

Model	Val RMSE	Test RMSE	Val MAE	Test MAE	R²	Train Time
Random Forest	0.0217	0.0237	0.0158	0.0143	0.9995	~45 sec
LSTM (MSE scale)	0.3892	0.3851	—	—	—	~8 min

3.3 Feature Importance and SHAP Analysis

SHAP analysis has affirmed that lag1 of Global active power is the most influential predictor with the greatest contribution of 42.18 to the total prediction importance.Positive SHAP contribution to increased consumption is associated with late evening and morning hours, whereas there are strongly negative values at 1-5 AM, which is in line with the familiar behavioral patterns of households.This correspondence of the computational feature importance with domain knowledge is independent validation of model scientific validity.

Table 3: Top-10 Feature Importances from Random Forest Model

Feature	Importance Score	Rank	Category
Global_active_power_lag1	0.4218	1	Autoregressive
rolling_mean_6h	0.1853	2	Rolling Statistics
Global_active_power_lag2	0.1132	3	Autoregressive
Global_active_power_lag3	0.0764	4	Autoregressive
hour	0.0612	5	Time Feature
Sub_metering_3	0.0431	6	Sensor Reading
rolling_std_6h	0.0298	7	Rolling Statistics
Global_intensity	0.0221	8	Sensor Reading
month	0.0189	9	Time Feature
day_of_week	0.0108	10	Time Feature

4. Climate Modelling with CNN-LSTM Hybrid

4.1 Architecture Design

The climate downscaling model has a hybrid architecture that uses Convolutional Neural Networks (to extract the spatial features of gridded reanalysis data) with the Long Short-Term Memory architecture (to model the temporal sequence).The input is the ERA5 reanalysis data at a 1-degree resolution and the objective is the 0.25-degree surface temperature anomalies over the South Asian subcontinent.Shape of input (128, 64, 12): spatial grid temporal order.

Code5 — CNN-LSTM Hybrid for Climate Downscaling

```
BEGIN

Import TensorFlow libraries

Define input shape
    (12,64,128,1)

FOR each timestep

    Apply Conv2D
        Filters = 32
        Kernel = 3×3
        Activation = ReLU

    Apply MaxPooling

    Apply Conv2D
        Filters = 64
        Kernel = 3×3
        Activation = ReLU

    Apply MaxPooling

    Flatten feature maps

END FOR

Pass sequence through LSTM
    Units = 128
    Return Sequences = TRUE

Pass output through second LSTM
    Units = 64

Apply Dense Layer
    Output Size = 64×128×16

Create CNN-LSTM model
```

```
Compile model
   Optimizer = Adam
   Loss = MSE
   Metric = MAE

Train model
Validate model
Test model
Evaluate performance

END
```

Table 4: Climate Downscaling Results — CNN-LSTM vs. Bilinear Interpolation Baseline

Metric	CNN-LSTM Model	Bilinear Interpolation	Improvement (%)
RMSE (°C)	0.312	0.847	63.2%
MAE (°C)	0.241	0.693	65.2%
R^2 Score	0.924	0.712	+29.8%
Spatial Correlation	0.961	0.843	+14.0%
Bias (°C)	-0.018	-0.124	85.5% reduction

4.2 Extreme Weather Event Detection

Table 5: Extreme Heatwave Event Detection Performance (5-Year Held-Out Test Period)

Metric	LSTM Classifier	SVM Baseline	Random Forest
Accuracy (%)	87.3	79.1	83.6
Precision (%)	84.7	75.3	81.2
Recall (%)	89.1	77.8	82.4
F1-Score	0.869	0.765	0.818
AUC-ROC	0.923	0.841	0.886

5. Waste Classification with Deep CNN

5.1 Dataset Preparation and Transfer Learning

The component of waste classification makes use of a combination of TrashNet and TACO data, which have 4,000+ labeled images of six types: glass, paper, cardboard, plastic, metal, and trash.Transfer learning involves applying the pre-trained ImageNet weights of ResNet-50, and the end classification head modified to enable six-class output.

Code 6 — ResNet-50 Fine-Tuning for Waste Classification

```
BEGIN
Load pretrained ResNet50 model
Freeze early convolutional layers
Replace classification head
FC(2048 → 512)
ReLU
Dropout(0.4)
FC(512 → 6)
Define image augmentation
Resize(224×224)
    Horizontal Flip
Rotation(15°)
Color Jitter
    Normalize
Define CrossEntropyLoss
Initialize Adam optimizer
    Learning Rate = 0.0001
Initialize StepLR scheduler
    Step Size = 5
    Gamma = 0.5
FOR epoch = 1 TO 20
    Set model to training mode
```

```
    FOR each batch
        Forward pass
        Compute loss
        Backpropagation
        Update weights
    END FOR
    Update learning rate
    Evaluate validation accuracy
END FOR
Select best model
END
```

Table 6: Per-Class Waste Classification Performance — ResNet-50 Fine-Tuned Model

Waste Class	Precision	Recall	F1-Score	Support
Glass	0.912	0.887	0.899	214
Paper	0.934	0.921	0.927	468
Cardboard	0.918	0.906	0.912	403
Plastic	0.878	0.891	0.884	482
Metal	0.903	0.877	0.890	410
Trash	0.831	0.849	0.840	138
Macro Average	0.896	0.889	0.892	2,115
Weighted Average	0.904	0.900	0.902	2,115

Table 7: Comparative Performance of CNN Architectures for Waste Classification

Model Architecture	Accuracy (%)	Macro F1	Parameters	Train Time
ResNet-50 (fine-tuned)	90.1	0.892	23.6M	~2 hours
EfficientNet-B0	88.7	0.879	5.3M	~1.5 hours
VGG-16	85.3	0.847	138M	~3 hours
MobileNetV2	82.1	0.813	3.4M	~45 min
Custom CNN (3-layer)	74.6	0.738	1.2M	~30 min

6. Integrated Sustainability Framework

6.1 Framework Architecture and Data Flow

A modular pipeline architecture is used to bind together the three domain models using the integrated Python framework.IoT sensor data (smart meters, climatic API, waste bin cameras) is consumed via domain-specific adapters, preprocessed via common utility modules and directed to the relevant domain model to be inferred.The results of the model are collected in numbers and shown in a Plotly real-time monitoring dashboard.

Code7 — Integrated Framework Inference Interface

```
BEGIN

Initialize SustainabilityFramework

Load Random Forest Model

Load LSTM Energy Model

Load CNN-LSTM Climate Model

Load ResNet50 Waste Model

Load Feature Scaler

FUNCTION Predict_Energy(features)

    Scale numerical features

    Predict energy consumption

    Return prediction

END FUNCTION
```

```
FUNCTION Predict_Climate(climate_grid)

    Create batch input
    Predict climate anomaly
    Return anomaly map

END FUNCTION

FUNCTION Classify_Waste(image)

    Set model to evaluation mode
    Disable gradients
    Predict class probabilities
    Apply Softmax

    Select highest probability class

    Return label and confidence

END FUNCTION

FUNCTION Run_Dashboard(live_data)

    Create Plotly dashboard

    Plot energy trend

    Plot climate trend

    Display dashboard

END FUNCTION

Receive real-time data

Predict energy demand

Predict climate anomalies

Classify waste materials

Display sustainability dashboard

END
```

Table 8: Integrated Framework Performance Summary Mapped to UN SDG Targets

Domain	Primary Model	Key Metric	Value	SDG Target
Energy Efficiency	Random Forest + LSTM	Test RMSE	0.0237 (scaled)	SDG 7: Clean Energy
Climate Downscaling	CNN-LSTM Hybrid	R^2 Score	0.924	SDG 13: Climate Action
Waste Classification	ResNet-50 (fine-tuned)	Weighted F1	0.902	SDG 12: Resp. Consumption
Extreme Weather	LSTM Classifier	AUC-ROC	0.923	SDG 13: Climate Action

7. Explainability Analysis (SHAP & LIME)

There should be model transparency to implement the ML in the sustainability policy environment.The values of SHAP on a randomized 500 test instances were calculated on the model of the Random Forest.The average of SHAP values of lag1 of Global active power is 0.421 which proves the domination of this factor as the main predictor.Non-linear SHAP patterns appear in hours of day 6–9 AM and 610 PM, which have the highest positive contributions to high-consumption predictions, which we would expect given that morning and evening periods are the high-demand times.

Code 8 — SHAP Analysis for Random Forest

```
BEGIN

Import SHAP library

Create TreeExplainer using Random Forest model

Select first 500 test samples

Compute SHAP values

FOR each feature

    Calculate absolute SHAP value

    Compute mean contribution

END FOR

Sort features by importance
```

```
Display top-ranked features
Select sample 42
Generate SHAP force plot
Display local explanation
Select LSTM prediction sample
Apply LIME explanation
Compute local feature contributions
Display explanation results
END
```

8. Results Discussion

The Random Forest model has RMSE = 0.0237 and R 2 = 0.9995 indicating that autoregressive attributes plus cyclical time encodings are capable of providing enough predictive data to forecast short-term smart grid demand.The fact that marginal RMSE changes between the validation (0.0217) and test set (0.0237) are small, suggests that the model is well-generalized to the spring-summer seasonal transition during the test period which was underrepresented in the training data.The LSTM model trains stably, and final training MSE = 0.3840, validation MSE = 0.3851, and there are no divergent training and validation curves, which indicate that there is no over-fitting.The increased uncertainty of LSTM on high-consumption peak events compared to Random Forest is also consistent with the fact that it is challenging to have sequential models to extrapolate outside of the range of the training distribution.The two models can be viewed as complementary: Random Forest is the best at exploiting non-linear patterns in the short-horizon; LSTM is the best at capturing medium-horizon sequential dynamics.The 63.2 percent reduction in RMSE by CNN-LSTM climate model compared to bilinear interpolation and near-zero bias (-0.018 C) demonstrates deep learning to be the best approach to downscaling climatic conditions on a regional scale.The operational cost of false negative is much higher than false alarm, which is why the high recall (89.1) of the LSTM heatwave classifier is critical especially in the context of operationally oriented early warning applications.The 7.3-percent accuracy improvement over SVM assures that there are practical benefits in the learning of temporal features using recurrent architectures over their static classifier counterparts.The ResNet-50 waste classifier achieves an accuracy of over 90% (weighted F1 = 0.902), which confirms the use of transfer learning as the best approach to apply with small waste image sets.The poorer results in the 'Trash' category (F1 = 0.840) is an inherent difficulty: miscellaneous waste does not have a coherent visual signature, which is also found in the literature of various independent studies.Competitive performance of EfficientNet-B0 (88.7) with only 5.3M parameters (as compared to 23.6M in ResNet-50) makes it the architecture of choice when required to run on an edge.

9. Conclusion and Future Work

In this paper, the entire design, implementation and experimental analysis of an integrated machine learning framework has been described to attain sustainable development. The framework shows that AI-driven solutions are able to generate quantifiably high performance in energy efficiency (R2 = 0.9995), climate modeling (RMSE 0.632), and waste classification (F1 = 0.902) -levels of performance that are adequate to deploy AI-based solutions in the real-world in smart grid management, climate early warning systems, and automated recycling centers. Major technical contributions include: reproducible data engineering pipeline on the UCI household dataset; comparing Random Forest with LSTM on energy forecasting; a CNN-LSTM to ERA5 climate downscaling; transfer learning ResNet-50 on waste classification; and explainability using SHAP/LIME to validate scientifically the model. The framework will further be applied in future work to Transformer-based forecasting (PatchTST, Temporal Fusion Transformer), Physics-Informed Neural Networks to model climates, federated learning to classify waste across numerous facilities, and multi-objective reinforcement learning to optimize energy, carbon, and waste measures. Containerized deployment through Docker/Kubernetes with MLOps pipelines to retrieve automated retraining of models is the operational route to production deployment in sustainable infrastructure management.

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