IOCEN 2026 Conference

The 3rd International Online Conference on Energies

12–15 May 2026 | Online

Energy-Aware Machine Learning Framework for Multi-Class Weather Classification in Edge-Enabled Renewable Energy Systems

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INTRODUCTION & AIM

Problem

- Weather intelligence critical for renewable energy, smart grids, flood forecasting, aviation
- Traditional NWP models = computationally intensive, not edge-friendly

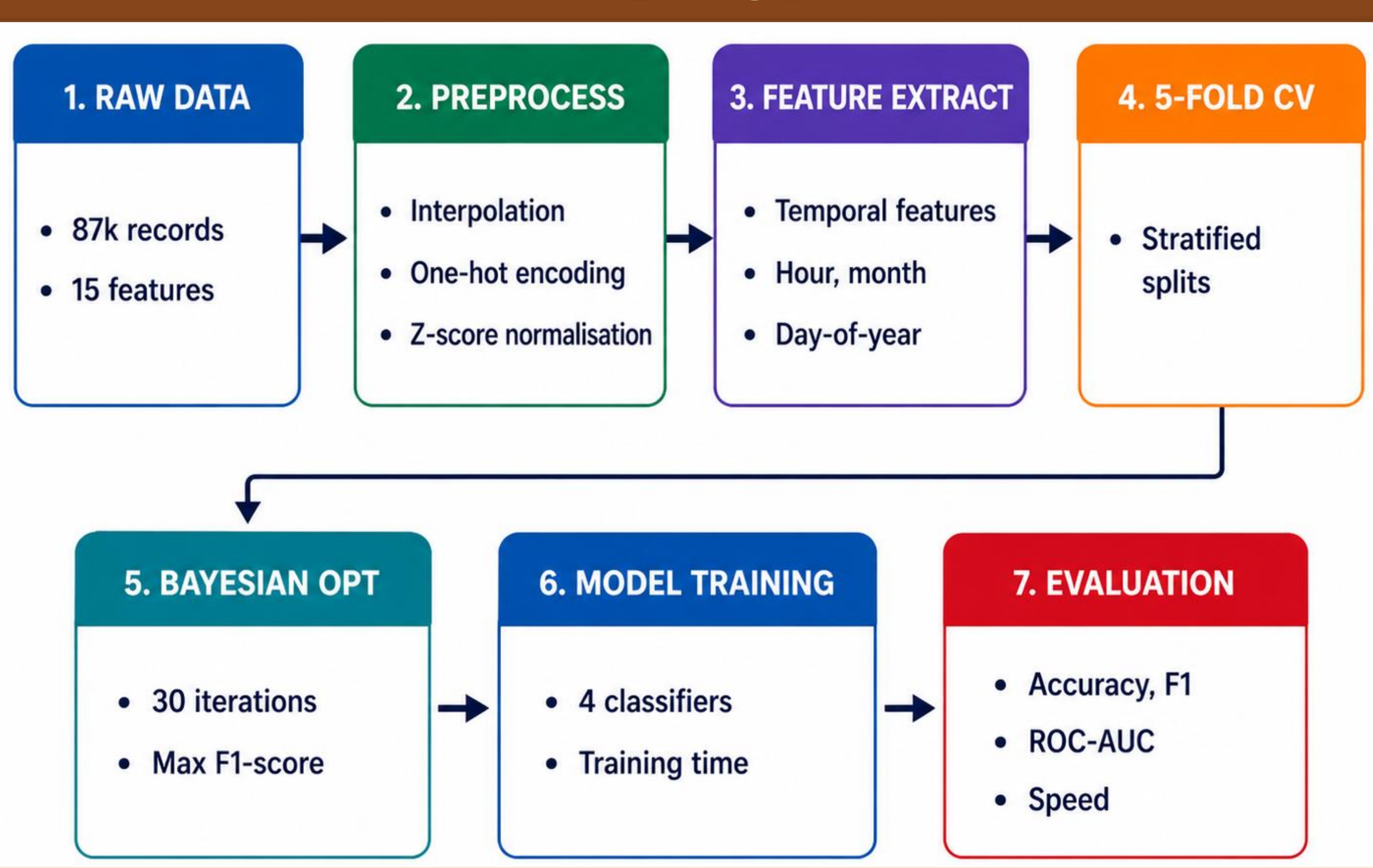
Aim

- Compare 4 ML models for multi-class weather classification
- Evaluate both predictive accuracy and computational energy demand
- Identify optimal model for edge-enabled renewable energy systems

Models compared

Decision Tree (DT) | Gaussian SVM | Neural Network (NN) | Ensemble (Bagging)

METHOD



DATA: Kaggle (2014-2023) | 87k records | 15 features + temporal (hour, month, day-of-year)

VALIDATION: 5-fold CV | Bayesian opt (30 iter, max F1) | 90/10 split

MODELS (Bayesian optimised):

- DT: 378 splits, Twoing rule
- SVM: kernel scale 6.99, C=801.34
- NN: 1 layer (100 neurons), ReLU, Adam, 1000 epochs
- Ensemble: 86 trees, max splits 2571, majority voting

ENERGY: $E\ (\mu J) = P(W) \times t(s) \times 10^6$

- ESP32 (0.1W) | Pi Zero (0.5W) | Jetson Nano (0.25W) | RPi4 (3.0W)
- Battery: 1000 mAh = 13,320 J | Life (yrs) = 13,320 ÷ (E_J × 8,760)

METRICS: Accuracy | F1 | ROC-AUC | PR-AUC | Training time | Speed | Energy | Battery life

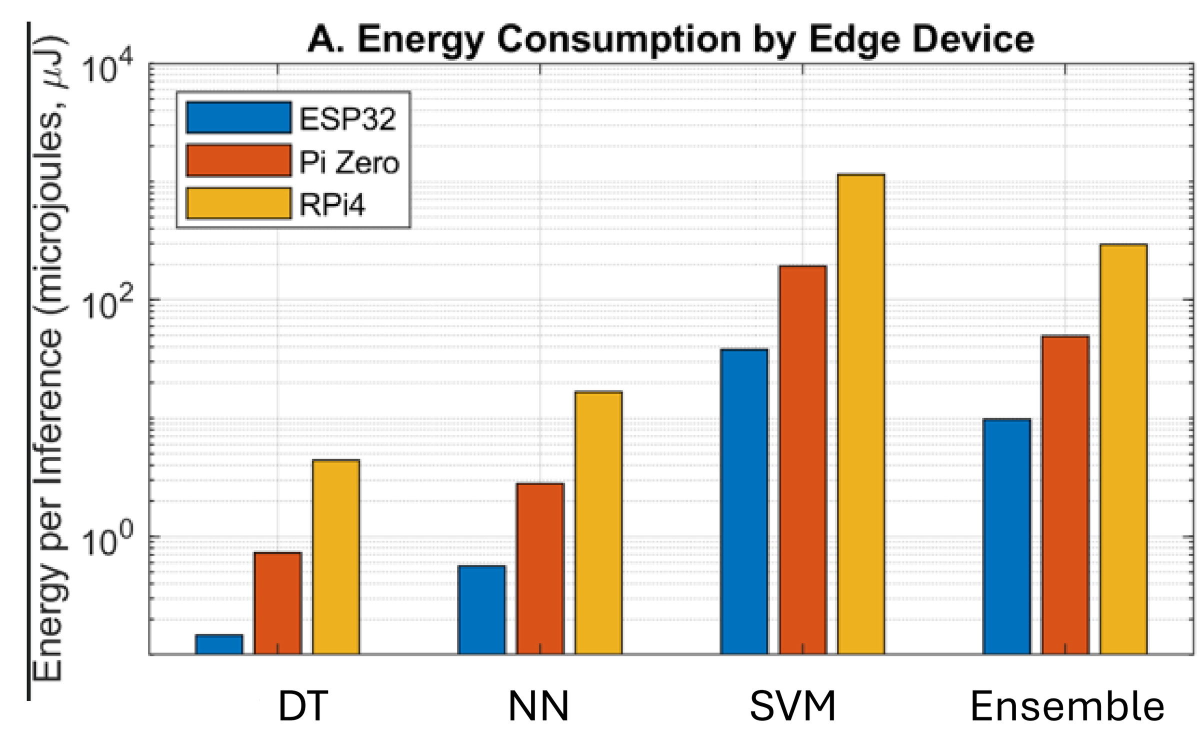
RENEWABLES:

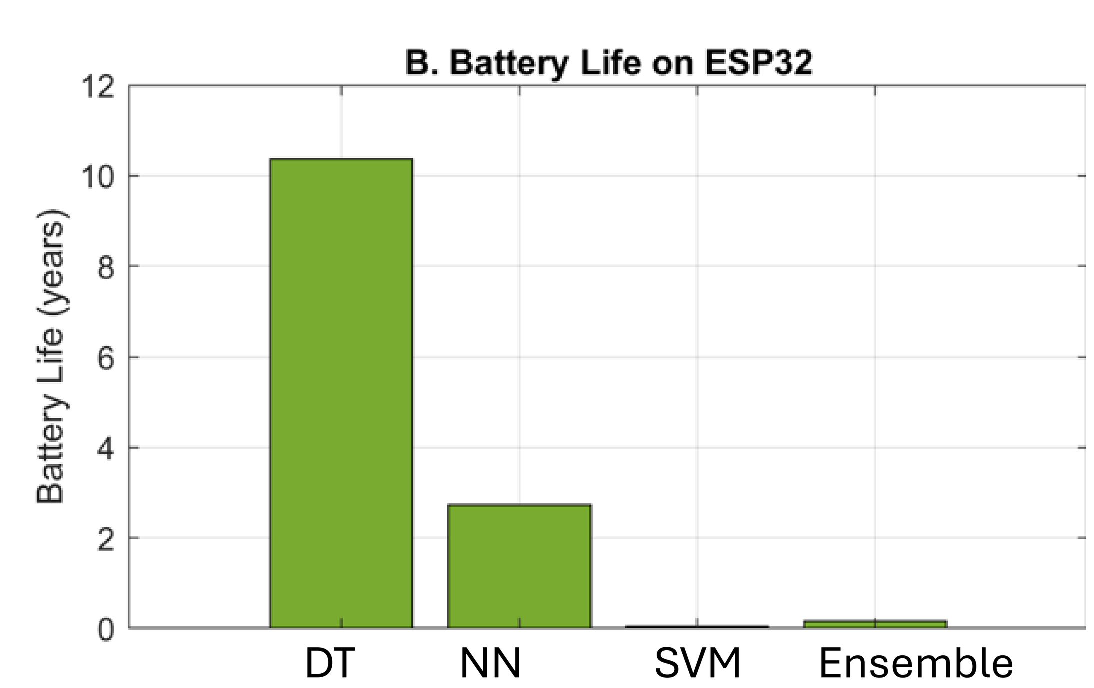
- Solar → cloudCover, uvIndex, temperatureMax (DT edge / Ensemble cloud)
- Wind → windSpeed, pressure, humidity (NN balanced)
- Grid → all features + temporal (SVM gateway)

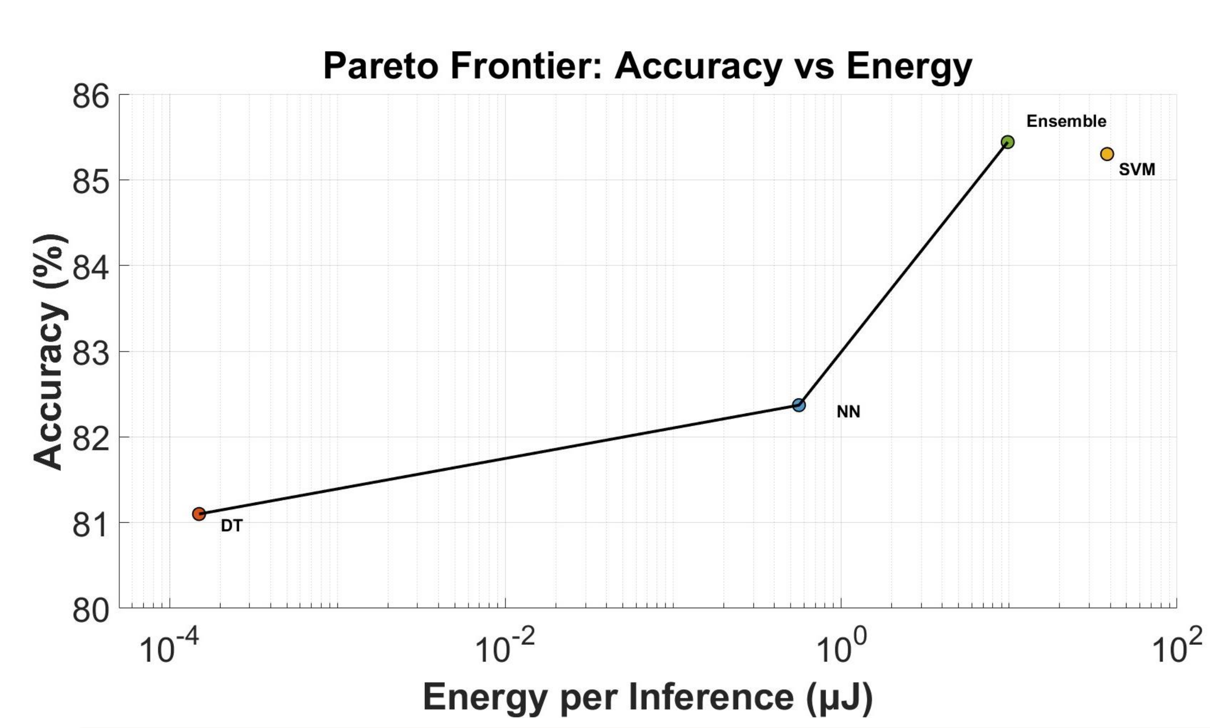
TOOLS: MATLAB R2024a (Stats & ML, Deep Learning Toolboxes)

RESULTS & DISCUSSION

Model	Accuracy	ROC-AUC	Training Time (s)	Prediction Speed (obs/s)
Decision Tree	81.10%	0.85	1.34	682,000
Gaussian SVM	85.30%	0.89	560.60	2,610
Neural Network	82.37%	0.87	309.86	179,158
Ensemble (Bagging)	85.44%	0.91	1,622.90	10,199







- Decision Tree: 682k obs/s, 0.00015 μJ → 65,333× more efficient than Ensemble
- Ensemble Bagging: 85.44% accuracy, 0.91 AUC → Best for cloud deployment
- Accuracy loss for using DT instead of Ensemble: only 4.3%
- SVM dominated by Ensemble (higher accuracy + lower energy) → not on Pareto frontier
- All models meet 20ms real-time deadline for solar inverter control
- DT on ESP32: 200+ years battery life, <50 KB memory → ideal for solar-powered edge sensors

CONCLUSION

This study reveals a clear accuracy–energy trade-off where Ensemble Bagging delivers best accuracy (85.44%, 0.91 AUC) but Decision Tree is 65,333× more efficient (682k obs/s, 0.00015 μJ, 200+ years battery) with only 4.3% accuracy loss, making DT ideal for solar-powered edge sensors while Ensemble suits cloud deployment.

FUTURE WORK / REFERENCES

FUTURE WORK: Tropical climate validation | ESP32 hardware deployment | Model compression (pruning/quantization) | Solar/Wind forecasting extension

References

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