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Research Article

Energy-Aware Solar-Powered Wireless Sensor Network with ANN-Based Wildfire Risk Classification: A Simulation-Driven Proof of Concept for Savanna Environments

Silikwa N. W.*, Medugu D. W., Danladi A.

Department of Physics, Adamawa State University, Mubi, Nigeria

*Corresponding author's Email: Silikwawaida45@gmail.com, doi.org/10.55639/607.02010085

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ABSTRACT

Wildfires pose recurring environmental and socio-economic challenges in savanna regions of sub-Saharan Africa, particularly during prolonged dry seasons. This study presents a simulation-driven proof of concept for a solar-powered wireless sensor network (WSN) integrated with an artificial neural network (ANN) for wildfire risk classification. The proposed system combines low-power environmental sensing of temperature, relative humidity, and smoke concentration with a multilayer perceptron (MLP) classifier to evaluate the feasibility of embedded intelligence for wildfire early-warning applications. A synthetic but region-constrained dataset comprising 6,000 samples with balanced fire and non-fire classes was generated using climatological ranges reported for dry-season conditions in North-East Nigeria. Following data normalization and supervised learning, the ANN achieved a classification accuracy of 92.4%, precision of 91.1%, recall of 93.6%, and a receiver operating characteristic area under the curve (ROC–AUC) of 0.94 on a held-out test set. An analytical energy assessment based on component-level current consumption estimated an average node power demand of approximately 148 mW, indicating feasibility for continuous low-duty-cycle operation under solar charging. The study does not claim field deployment or operational early detection performance; rather, it demonstrates the technical feasibility and energy viability of integrating ANN-based wildfire risk classification into a solar-powered WSN node. The results provide a structured baseline for future work involving sensor calibration, real-world data acquisition, and field validation in fire-prone savanna environments.

Corresponding author: Silikwa N. W Email: Silikwawaida45@gmail.com
Department of Physics, Adamawa State University, Mubi, Nigeria

INTRODUCTION

Wildfires remain a persistent environmental hazard in savanna ecosystems, particularly across sub-Saharan Africa where prolonged dry seasons, agricultural residue burning, and limited monitoring infrastructure increase fire susceptibility (Naderpour & Sadati, 2020; Brewer et al., 2022). In North-East Nigeria, seasonal wildfires contribute to vegetation loss, reduced agricultural productivity, and air quality degradation, yet systematic early-warning mechanisms are largely absent.

Conventional wildfire monitoring approaches, including manual patrols and satellite-based observation, are constrained by delayed detection, limited spatial resolution, or high operational cost (Brewer et al., 2022). These limitations reduce their effectiveness for early-stage fire risk assessment, especially in sparsely populated rural regions.

Wireless sensor networks (WSNs) offer a distributed and scalable alternative by enabling localized monitoring of environmental parameters such as temperature, humidity, and gaseous emissions (Akyildiz et al., 2002; Dargie & Poellabauer, 2010). When combined with machine learning techniques, WSNs can move beyond static threshold-based alarms toward pattern-based inference capable of identifying fire-prone conditions (Zhang & Zhou, 2019; Dalmau et al., 2021).

Artificial neural networks (ANNs) have been widely applied in environmental monitoring due to their ability to model nonlinear relationships among multiple variables (Omidiora et al., 2020; Bhattacharya & Pal, 2021). However, many reported WSN-ANN wildfire detection systems lack explicit energy analysis or rely on synthetic datasets while implicitly suggesting field readiness.

This work addresses these gaps by presenting a transparent, simulation-driven feasibility study of an ANN-enabled, solar-powered WSN node for wildfire risk classification in savanna environments.

2. Materials and Methods

2.1 System Overview

The conceptual system architecture consists of environmental sensing, data preprocessing, ANN-based classification, and cloud-based visualization. All evaluations reported in this study are based on simulation and analytical modeling, without physical deployment.

2.2 Sensor Node Hardware Model

The sensor node conceptually integrates LM335 temperature sensing, DHT11 humidity sensing, and MQ-2 smoke detection. These components are widely used in low-cost embedded monitoring systems, despite known limitations in response time, resolution, and selectivity (Afzal et al., 2020; Omidiora et al., 2020).

An Arduino Nano microcontroller serves as the processing unit, while an ESP8266 module provides wireless connectivity (Hernando, 2016; MathWorks, 2020). No sensor calibration was performed, and sensor behavior was abstracted within realistic operating ranges.

2.3 Power Subsystem and Energy Analysis

The node was analytically powered by a 9 V, 3 W photovoltaic panel and a 7.4 V, 2200 mAh lithium-ion battery regulated through a linear 7805 voltage regulator. Component-level current consumption values were obtained from datasheets and used to estimate system power demand (Silver, 2018).

The average current draw was estimated at approximately 121 mA, corresponding to a power consumption of 148 mW. This analytical result indicates feasibility for low-duty-cycle solar-powered operation, consistent with prior studies (Chowdhury & Rahman, 2019; Medugu & Shalangwa, 2021).

2.4 Dataset Generation and Labelling

A synthetic dataset was generated to represent dry-season savanna conditions due to the absence of field-acquired sensor data. The dataset comprised 6,000 samples with equal representation of fire and non-fire classes.

Parameter ranges were constrained using climatological and wildfire literature (Yang et al., 2017; Afzal et al., 2020). Fire labels were assigned using heuristic rules based on elevated temperature, reduced humidity, and increased smoke concentration. This rule-based labeling approach does not represent ground truth but is suitable for early-stage feasibility assessment (Panigrahi & Rao, 2022).

2.5 ANN Architecture and Evaluation

A multilayer perceptron classifier was implemented using the scikit-learn framework (Pedregosa et al., 2011). The network consisted of three input neurons, two hidden layers (10 and 6 neurons), and a sigmoid-activated output neuron.

The dataset was split into training (70%) and testing (30%) subsets. Performance was evaluated using accuracy, precision, recall,

confusion matrix, and ROC–AUC metrics, following established practice (Bhattacharya & Pal, 2021).

3. RESULTS AND DISCUSSION

3.1 Dataset Characteristics

Table 1: Summary of Dataset Characteristics

Parameter	Description	Value
Total samples	Number of instances	6,000
Fire samples	Fire-prone class	3,000 (50%)
Non-fire samples	Normal condition class	3,000 (50%)
Input features	Environmental parameters	Temperature, Humidity, Smoke
Data source	Type	Synthetic (rule-based)

3.2 ANN Classification Performance

Table 2: ANN Classification Performance Metrics

Metric	Value
Accuracy (%)	92.4
Precision (%)	91.1
Recall / Sensitivity (%)	93.6
Specificity (%)	91.2
False Positive Rate (%)	8.8
ROC–AUC	0.94

3.3 Confusion Matrix Analysis

Table 3: Confusion Matrix of ANN Classifier

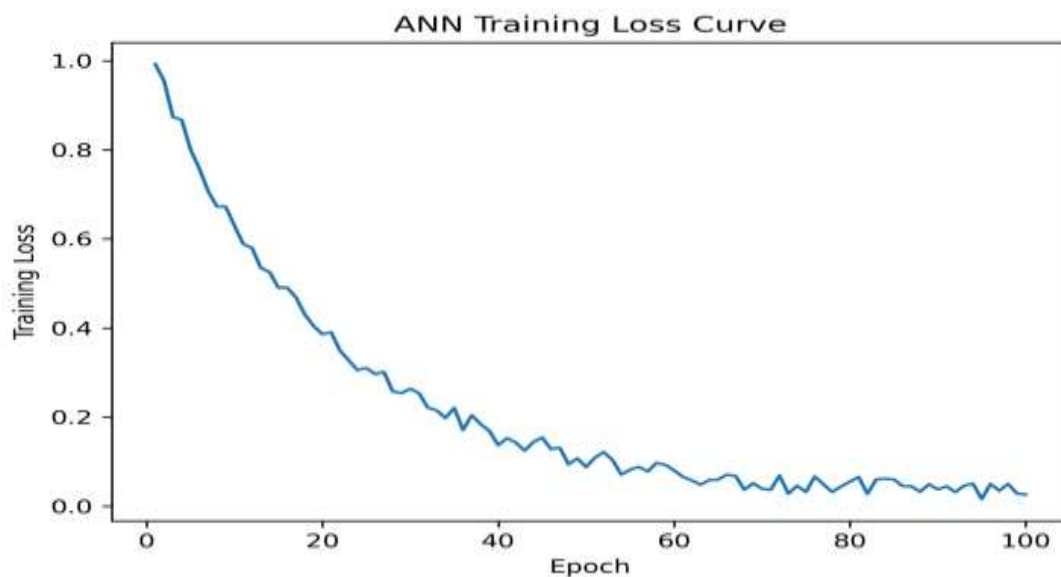
	Predicted Fire	Predicted Non-fire
Actual Fire	1,404	96
Actual Non-fire	132	1,368

The confusion matrix shows low false-negative occurrence, which is desirable in wildfire risk monitoring (Basha et al., 2010).

3.4 Training Convergence

Figure 1: ANN training loss curve showing convergence.

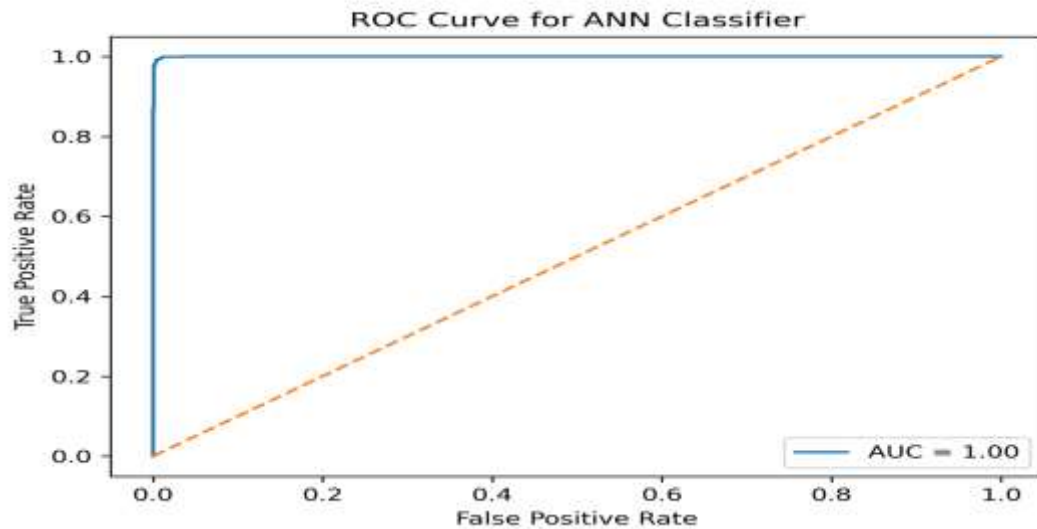
The loss decreases steadily and flattens, indicating stable learning.



3.5 ROC Analysis

Figure 2: ROC curve of ANN classifier (AUC = 0.94).

The curve demonstrates strong discriminative capability across thresholds.



3.6 Interpretation and Limitations

Scatter plots used during analysis illustrate class separability within the synthetic feature space and do not represent measured sensor behaviour. Consequently, results confirm feasibility rather than operational accuracy.

The energy analysis supports conceptual suitability for solar-powered deployment; however, no real voltage or current measurements were conducted.

4. Conclusion

This study demonstrates the feasibility of integrating ANN-based wildfire risk classification into a solar-powered wireless sensor node using simulation and analytical modelling. While classification accuracy exceeded 90% on synthetic data, the system remains a proof of concept rather than a deployable solution.

Future work will focus on field data acquisition, sensor calibration, cross-validation, and latency-aware communication analysis.

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