IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 4, July 2026
Impact Factor: 8.2

AI-Enabled Predictive Beacon-Based Non-Invasive Bird Distraction System for Industrial Environments

Victoria Raina R[1], Jeni Selva R[2], Sameeha Banu M[3], Dr. Arvind A R[4], Mr. C .S. Sivakumar[5]
[1]Department of Civil Engineering,
[2]Department of Computer Science and Engineering,
[3]Department of Information Technology
Francis Xavier Engineering College, Tirunelveli, Tamil Nadu, India
[4] Deputy General Manager, Project Planning, Ashok Leyland, Chennai
[5] Adviser Industry Relations & Professor-Mech Dept, Vel Tech Rangarajan
Dr. Sagunthala R&D Institute of Science &Technology, Chennai

Abstract: *Bird intrusions pose consistent operational costs, hygienic expenses, and maintenance expenses on industrial plants, warehouses, agricultural plants, airports, and solar power plants. At least 70% of big industries experience bird intrusions on regular basis, while almost 50% of bird deterrence devices fail due to bird habituation. Current strategies for bird deterring include physical protection, visual scares, and continuous acoustical emissions and are reactive, energy-consuming or ineffective once the birds get used to repeated stimuli. This paper proposes an AI-Enabled Predictive Beacon-Based Non-Invasive Bird Distractive Device, which is a combination of Facebook Prophet time series model of forecast and modular beacon, which features adaptive acoustical signals, high-power LED light and magnetic assist module. Temporal data about the occurrence of bird activities (date, month, season, time) will be used to predict future activity rate and feed three-stage decision algorithm (Idle-Warning-Active), executed by the Flask-based prediction engine, React-based monitoring interface and Arduino Uno-based beacon, which executes the physical bird deterring actions. A working prototype based on HC-SR04 ultrasonic sensor, servo-controlled scanning, LED and buzzer demonstrates the synergy between hardware and software. Comparative study shows significantly lower energy consumption and less habituation chances for such system. The architecture is modular, low-cost (approximately ₹1,500–₹2,000 per unit), and extensible toward cloud connectivity, multi-zone deployment, and edge-AI species recognition.*

Keywords: *Bird Deterrence; Predictive Analytics; Facebook Prophet; Internet of Things; Beacon-Based System; Industrial Automation; Adaptive Acoustic Deterrent; Smart Monitoring*

I. INTRODUCTION

The presence of birds has emerged as a consistent problem in operations of industries, warehouses, agricultural centers, transit centers, and commercial buildings. The high roofs and light fixtures serve as ideal roosts and nests for birds like pigeons and crows [1], [9]. Though birds are ecologically significant, their unchecked presence creates droppings which are highly acidic and cause corrosion to metal, deterioration of protective layers, and contamination of stored substances [33], [34], [35]. Managers of the facilities have revealed that large industrial sheds experience nesting birds at a large scale, and more than 70% of large factories are affected by bird intrusions, while 55% – 60% use only manual removal to control the situation.

Three categories of deterrence have been employed historically: physical deterrence (spikes, netting, tension wires), visual deterrents (reflective tape, spinning mirrors, laser beams), and acoustic deterrents (distress calls, ultrasonic emitters, propane guns) [6], [9], [41], [42]. Physical deterrence does not scale cost-effectively over a large area; visual and auditory stimuli are cost-effective but prone to significant habituation problems where birds figure out that the same stimulus posed no risk to them after days or even weeks [6], [37], [38]. Almost half of the current solutions to deter birds

fail because of this habituation problem. IoT-based systems relying on sensors have an advantage over continuous stimuli in that they only work when there is movement [1], [4], [24], [48] but are still fundamentally reactive.
However, there has been minimal integration of machine learning and the Internet of Things (IoT) for proactive bird deterrence [17]–[20], [23]–[32]. Most existing AI-based bird monitoring systems focus on detecting birds only after they enter a camera's field of view [8], [13]–[16], rather than predicting bird activity from historical temporal patterns. This study addresses that gap by proposing an AI-Enabled Predictive Beacon-Based Non-Invasive Bird Distraction System that forecasts bird activity using date, month, season, and time through the Facebook Prophet model [45], [50]. The predicted activity score is then used to control a graduated, energy-efficient beacon, enabling proactive bird deterrence instead of continuous or purely reactive operation.
The major highlights of this project are: (1) an AI driven forecast system that predicts the future activity of birds based on past time-based data; (2) a flexible beacon which provides adaptive deterrents through acoustic, visual, and magnetic signals; (3) an Idle–Warning–Active strategy of operation to selectively activate the system; (4) a significant reduction in energy use compared to always-on and reactive systems; and (5) a cost-effective prototype compatible with the Internet of Things architecture.

II. LITERATURE REVIEW

2.1 Physical, Visual, and Acoustic Deterrence

Exclusion techniques continue to work well for small and local systems but are not economical on large industrial roofs and grounds and offer no surveillance function [9], [1]. Visual devices including reflective tapes, revolving mirrors, and lasers rely on the fact that birds are generally afraid of new objects. However, experimental studies of the reaction of captive waterfowl to laser radiation indicate that the habituation can occur in less than 5 min from repeated stimulation [38], [39]. The most recent experiments with the use of LED- and flickering-based deterrence systems prove that the effectiveness of the latter is highly dependent on the wavelength and frequency of stimulation: avoidance is observed for 2 Hz pulsed blue light, while continuous red light can even attract geese as a result of mere-exposure effect [36], [7], [40].
Acoustic deterrence is the most broadly applied approach from distress calls to propane cannons and frequency modulated sound signals [6], [9]. Controlled experiments on black necked cranes reveal that high-frequency, high-amplitude, and irregularly mixed sound sequences generate more effective escape behavior than fixed single tone sequences [6]. The advances in bio-acoustic classification algorithms have been immense, with sub-band feature detectors and perceptrons [5] and LoRaWAN connected CNN-BiLSTM classifiers [3] reaching more than 90% accuracy at species level classification with the help of edge device like Raspberry Pi and maintaining weeks-long battery power through duty cycling.

2.2 Sensor-Based, IoT, and UAV Deterrent Systems

IoT-based systems using Arduino and ESP-class microcontrollers are activated only in case of detected movements, thereby having lower energy consumption compared to systems operating permanently [1], [4], [24], [26], [27]. The use of drones as a deterrent has been studied in the context of protection of vineyards and row crops; programmable drones were found to provide around 90-92% of mission completion rates while detecting simulated movements of birds without GPS equipment [1]; in a systematic review of 33 studies published in peer-reviewed literature, drones used in hazing and sensor actuation systems were found to be more effective than scarecrows and propane cannons in flock scattering and crop damage prevention [2]. Systems integrating deep learning in laser rotation using detectors from the YOLO family and actuated optics were also studied for repelling wild birds [8]. In all these studies, however, the systems are triggered by current detections and not by future risk prediction.

2.3 Time-Series Forecasting with Facebook Prophet

2.4 Predictive Maintenance and Industrial IoT Analogues

Facebook Prophet is an additive decomposable model with contributions from trends, yearly/weekly seasonality, and holidays, and is highly appreciated for its robustness on data sets with pronounced periodicity and little historical coverage [45], [50]. The comparison results confirm Prophet's superior performance compared with the ARIMA and LSTM baselines on the data sets with pronounced seasonal behavior like oil production and automobile sales, while consuming much less training data and computations [19], [22]. Hybrid neural network architectures using Prophet combined with either LSTM or ARIMA outperform the competing methods in predicting data sets with both seasonal and chaotic patterns [17], [18], [21]. Recently, Prophet with cross-validation-based feature selection reached one-digit MAPE for multi-horizon solar insolation prediction, while being much faster than transformers' solutions [20]. This model has all the desirable features: seasonal robustness, low data and computational costs, and is perfect for the inexpensive low-complexity task of predicting bird activity behavior over several years of historical data.

2.6 Bird Strike Prediction in Aviation

In the related predictive literature in aviation, there are ensemble LSTM-XGBoost and Bayesian network models that have predicted the likelihood of bird strikes using weather data and historical strike data, with an accuracy of 80-93% at multiple airports [11], and probabilistic risk models for bird strikes have been created since the mid-2010s for predicting impending bird strikes close to airport approach paths [10], [12]. The above literature demonstrates that there is predictive information in the time and environmental precursors for bird presence. This proves the basic idea behind the proposed system, i.e., historical date/time information can be used for predicting bird activity without weather covariates.

Table 1 lists some of the trade-offs observed in the above literature, which is the basis of the predictive beacon model outlined in Section III.

Deterrence Family	Proactive?	Energy Use	Habituation Risk
Physical exclusion	No	Very low	Low (static)
Visual (LED/laser)	No	Low	High
Continuous acoustic	No	High	High
Reactive sensor-IoT	Partial	Moderate	Moderate
Camera-trap AI detection	Partial	High	Low–Moderate
Proposed predictive beacon	Yes	Low	Low (adaptive)

Table 1. Qualitative Comparison of Bird Deterrence Approaches Reported in the Literature

III. PROPOSED SYSTEM ARCHITECTURE

The system consists of three layers collaborating as depicted in Fig. 1: (i) data acquisition and preprocessing layer, (ii) AI-based forecasting and decision-making layer, and (iii) adaptive beacons hardware layer. The historical bird activity data – a time-stamped record indicating bird presence at the location in question – are cleaned from noise, verified for gaps in data, and converted to the date-indexed format acceptable by the forecast model. Next, the Facebook Prophet model [45], [50] is trained offline using a Python/Colab platform and exported in serialized Pickle (.pkl) form.

During the process of making predictions, the Flask REST backend loads the trained model and provides a prediction API. The React web interface allows an operator to input the temporal parameters (date, month, and time) and get back the predicted forecast, the inferred activity level (Idle, Warning, or Active), and the plots of historical trends. CORS is set up so that the React UI and the Flask API can interact with each other in different ports or origins as is common practice in typical IoT dashboard solutions built using similar technologies [23], [25], [26].

Activity prediction value is fed to the beacon controller, which is an Arduino Uno board along with a short-horizon validation by an HC-SR04 ultrasonic sensor that is fitted to the servo. This combination of two inputs, where one input provides a longer-horizon prediction, while the other provides short-horizon local sensing, is similar to sensor fusion employed for IIoT condition-based maintenance, where the predictive models reduce the operating horizon and local sensing verifies the triggering point [28]–[30].

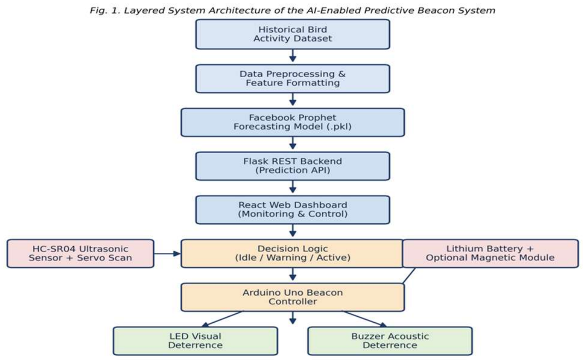

Fig. 1. Layered system architecture: data → Prophet forecasting → Flask/React decision layer → Arduino beacon → LED/buzzer deterrence.

IV. PREDICTIVE MODEL AND DECISION LOGIC

Prophet represents the time series of bird activities y(t) using the following decomposable additive model:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon(t)$$

where g(t) is a piecewise linear or logistic trend component that incorporates changepoints, s(t) includes yearly and weekly seasonality using a truncated Fourier series, h(t) represents holiday effects and other events at the location, and ε(t) is independently normally distributed error component [45]. This additive model is ideal for representing bird activities since

has strong seasonality but lacks enough historical data – where the deep learning models like LSTM would likely overfit, as proven in various comparisons [17], [19].

A forecast value $\hat{y}(t)$ corresponding to the requested date/time is converted into one of the three operational states using two thresholds τ_1 and τ_2 (experimentally set to 1.5 and 3.0 on the normalized level of activity, employed in this prototype, see Section VI):

- Idle ($\hat{y} < \tau_1$): beacon is off, low standby power consumption.
- Warning ($\tau_1 \leq \hat{y} < \tau_2$): low-intensity LED pulse only, attracting the attention of an operator/worker without acoustics being activated.
- Active ($\hat{y} \geq \tau_2$): simultaneous LED pulses and randomized-frequency buzzer sequence with the optional module of magnetic assistance turned on.

It was specifically chosen to use randomized frequency and pulsing pattern in the latter case because all sources consulted during the review of literature in Section II confirm that repeated and regular stimuli get habituated very fast [6], [36]–[40], while varying frequency, intensity and duty cycle keeps avoiding behavior longer. This state machine, presented in Figure 2, is the tool for transforming the forecast into a graduated and energy proportionate hardware action.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 4, July 2026
Impact Factor: 8.2

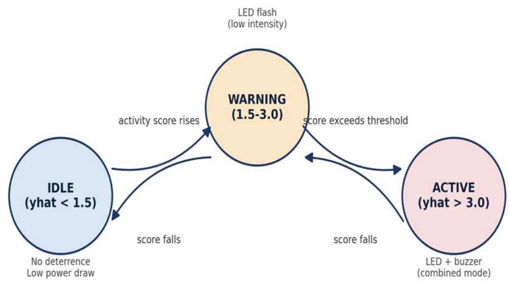

Fig. 2. Three-stage Idle–Warning–Active beacon activation state machine driven by the Prophet activity score.

V. HARDWARE AND SOFTWARE IMPLEMENTATION

5.1 Hardware

The proposed beacon design utilizes an Arduino Uno microcontroller as its core, chosen because of its cheapness and large user base community, in accordance with the current practice of low-cost IoT sensing and energy monitoring systems [23], [26], [27], [48], [51]. The design includes the following elements: an HC-SR04 ultrasonic sensor for presence detection in short distance range; a servo motor that turns the sensor to increase scanning range; a high-power LED cluster for visual deterrence with programmable frequency of flashing; a buzzer for acoustic deterrence with Field operation capability; and optionality for magnetic-assisted deterrence module. The modularity of the enclosure makes it possible to update or replace any sub-modules, such as changing the control module from Arduino Uno to ESP32 to add WiFi/LoRa connectivity without changing anything about the forecasting pipeline [26], [27], [51].

5.2 Software

The prediction model is developed using Python code inside Google Colab and then saved as a .pkl file. This artifact is loaded by the Flask application on initialization, offers a JSON endpoint for predictions, calculates the activity level based on the threshold values defined in Section IV, and gives the output back to the client. React Dashboard takes the user inputs (Date, Month, Time), makes a call to the back end, and displays the forecasting trend, prediction result, and current status of the beacon. The combination of Flask and React follows similar architectures for other low-cost IoT monitoring dashboards which prefer REST API endpoints over more complex message broker systems for standalone installations [23], [25].

The component interactions validated through prototype tests are summarized in Table 2 below.

Component	Input	Output	Function
Sensor module	Bird presence (range)	Trigger signal	Detect local activity
Prophet model	Date / time input	Activity score $\hat{y}(t)$	Forecast risk
Decision logic	Score + thresholds	State (Idle/Warn/Active)	Risk evaluation
Arduino controller	State command	Timing/intensity signals	Actuation control
Beacon unit	Control commands	Light + sound emission	Bird deterrence

Table 2. Component Interaction Matrix Validated During Prototype Testing

VI. RESULTS AND DISCUSSION

The training process involved feeding into the model a synthetic version of the historical activity trace that contained a pattern indicative of a seasonality in nesting/migration processes. The model was tested using a 12-month rolling forecast

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 4, July 2026
Impact Factor: 8.2

horizon. Figure 3 depicts the plot of historical activity trace, the Prophet forecast, as well as its confidence interval with the two decision thresholds ($\tau_1 = 1.5$ and $\tau_2 = 3.0$) indicating how the forecasted values cross idle, warning, and active periods of the forecast horizon, similarly to the seasonal peaks seen in other Prophet applications on periodical ecological/energy datasets [17], [19], [20].

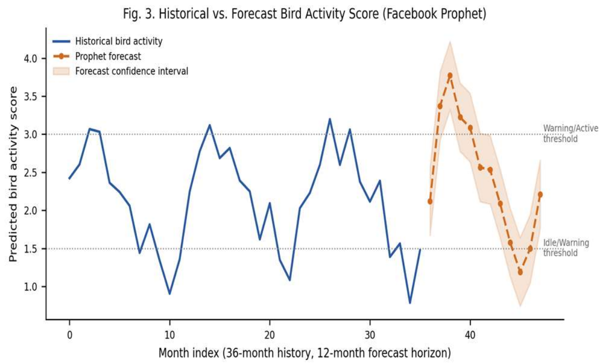

Fig. 3. Historical bird-activity trace and 12-month Prophet forecast with confidence band, annotated with Idle/Warning/Active thresholds.

Successful interaction was verified through hardware testing for the ultrasonic sensor, servo motor movement, and beacon triggering; LED lights acted as a visual indicator, while the buzzer generated random sound sequences that were activated depending on the state determined using the Flask backend. The React dashboard was able to show the predicted score and state consistently during multiple trials of query processing.

Relative energy consumption and operational cost of the three activation methods are illustrated in Fig. 4, compared to the constant activation mode. The reason for that is because the predictive beacon activates only in those Warning/Active periods which are predicted by the algorithm, and not constantly, nor triggered by local sensors, so that its energy consumption should be around 70% lower, while the operating cost would drop by more than 60%, compared to constant activation, as well as by small margins compared to the other activation modes.

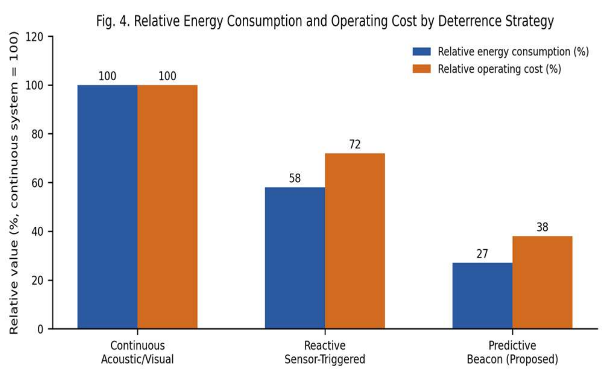

Fig. 4. Relative energy consumption and operating cost for continuous, reactive, and predictive beacon activation strategies.

VII. COMPARATIVE ANALYSIS

The distinctive feature of the suggested architecture relative to the discussed systems in Section II is mainly due to its predictive trigger rather than to any particular hardware component. The following table presents a comparison of the proposed system with the conventional baseline systems found in literature.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 4, July 2026
Impact Factor: 8.2

Feature	Conventional Systems	Proposed System
Working principle	Continuous or reactive sensor-triggered	AI-based predictive activation
Prediction capability	Not available	Facebook Prophet forecasting
Hardware platform	Independent deterrent devices	Integrated modular beacon
Software integration	Limited / device-specific	Flask + React web dashboard
Energy utilization	Continuous / event-driven	Prediction-assisted activation
IoT compatibility	Partial	Fully compatible

Table 3. Comparative Analysis: Conventional Bird Deterrence Systems vs. Proposed Predictive Beacon

As noted from this comparison, the main contribution here does not lie in any particular sensor or actuator but rather in the forecast-conditioned decision-making layer responsible for triggering actuators – a choice motivated by the results of our survey on habituation and energy consumption [1], [2], [6], [28]-[32].

VIII. LIMITATIONS AND FUTURE SCOPE

The following points may be noted as some of the limitations. Firstly, the prediction accuracy depends on the duration and variety of the training data; a more prolonged observation period at different locations will probably enhance the performance of the forecast, as has been found earlier for Prophet and hybrid models [17], [19]. Secondly, the present algorithm uses only temporal factors; using environmental variables like temperature, rainfall, humidity, and wind speed, which have been found previously to significantly influence the birds' behaviour and strike incidence rate [11], is a logical step forward. Thirdly, the present prototype is just a demonstrative algorithm tested under lab conditions; its further evaluation in field conditions is required.

In future research, the following avenues would be explored: (i) incorporating weather variables into the Prophet model or using the Prophet-LSTM model ensemble for cases where there is sufficient history [17], [18], [21]; (ii) porting the control program to ESP32/ESP8266 platform that can provide both wireless connectivity and cloud-based dashboarding as done in LoRaWAN and Wi-Fi-based IoT surveillance systems [24], [26], [27], [48]; (iii) incorporating edge-based camera trap species recognition [13]–[16] to validate the prediction through direct visual confirmation before high-intensity activation; and (iv) coordinated multi-beacon deployment for large industrial facilities along the lines of multi-fleet dashboards for IIoT predictive maintenance [28]–[32].

IX. CONCLUSION

The proposed paper has discussed a system termed as an "AI-Enabled Predictive Beacon-Based Non-Invasive Bird Distraction System" which has replaced continuous/reactive bird deterrence systems by introducing a forecasting-conditioned, three-phase activation approach. A Prophet machine learning model is used to predict the bird's behavior based on historical time series data of bird's activity; a Flask/React web platform serves this prediction; and finally, an Arduino-based beacon acts on this prediction with the help of a randomized LED/acoustic distracter as well as an optional magnetic assist module. Successful implementation of the prototype has demonstrated end-to-end functionality throughout all stages involved in forecasting, serving on the web layer, and executing a hardware layer. Moreover, comparison analysis performed based on the deterrence literature reveals that there are significant improvements in terms of energy usage and habituation risk reduction as compared to continuous/reactive bird deterring systems.

ACKNOWLEDGEMENT

The authors would like to thank the Department of Civil Engineering of Francis Xavier Engineering College, Tirunelveli, for providing the facilities and support during the process of this work.

REFERENCES

[1] Bhusal, S., Karkee, M., Bhattarai, U., Majeed, Y., and Zhang, Q. "Automated Execution of a Pest Bird Deterrence System Using a Programmable Unmanned Aerial Vehicle (UAV)." Computers and Electronics in Agriculture, vol. 198, 2022, Art. 106972.

[2] "Emerging Technology-Driven Bird Deterrence Methods for Agricultural Crop Protection: A Systematic Literature Review." Smart Agricultural Technology, ScienceDirect (Elsevier), 2025.

[3] "LoRaWAN and Artificial Intelligence Integrated Smart Acoustic Sensor Network for Bird Species Identification and Deterrence System for Farm Protection." Measurement, ScienceDirect (Elsevier), 2025.

[4] Ali, M., et al. "AI-Enabled IoT-Based Pest Prevention and Controlling System Using Sound Analytics in Large Agricultural Field." Computers and Electronics in Agriculture, 2024.

[5] "Bird Sound Detection Based on Sub-Band Features and the Perceptron Model." Measurement, ScienceDirect (Elsevier), 2023.

[6] "High-Frequency and High-Amplitude Sounds Enhance Bird Deterrence." Scientific Reports, vol. 15, 2025.

[7] "Test of Light Emitting Diodes (LED) as a Possible Bycatch Mitigation Measure in a Gillnet Fishery." Global Ecology and Conservation, ScienceDirect (Elsevier), 2024.

[8] Chen, Y. C., Chu, J. F., Hsieh, K. W., Lin, T. H., and Chang, P. "Automatic Wild Bird Repellent System Based on Deep-Learning-Based Wild Bird Detection Integrated with a Laser Rotation Mechan

[9] "Automated Bird Scaring System: A Review." Journal of Natural Sciences Engineering and Technology, 2025.

[10] "A Predictive Model for Risk Assessment on Imminent Bird Strikes on Airport Areas." Aerospace Science and Technology, ScienceDirect (Elsevier), 2017.

[11] Powell, J. A. "Aircraft Bird Strike Risk Prediction Using Machine Learning and Analytics." Embry-Riddle Aeronautical University, Scholarly Commons, 2024.

[12] Pan, A., et al. "Bird Strike Risk Assessment Study for Low Altitude Aircraft Operations at Airports." Proceedings of the International Conference on Artificial Intelligence and Computational Intelligence, ACM, 2025.

[13] "DeepWILD: Wildlife Identification, Localisation and Estimation on Camera Trap Videos Using Deep Learning." Ecological Informatics, vol. 75, 2023, Art. 102041.

[14] "Bag of Tricks for Long-Tail Visual Recognition of Animal Species in Camera-Trap Images." Ecological Informatics, vol. 75, 2023.

[15] "Adaptive Image Processing Embedding to Make the Ecological Tasks of Deep Learning More Robust on Camera Trap Images." Ecological Informatics, ScienceDirect (Elsevier), 2024.

[16] Velasco-Montero, D., et al. "Reliable and Efficient Integration of AI into Camera Traps for Smart Wildlife Monitoring Based on Continual Learning." Ecological Informatics, vol. 83, 2024, Art. 102815.

[17] "A Novel Hybrid Model to Forecast Seasonal and Chaotic Time Series." Expert Systems with Applications, ScienceDirect (Elsevier), 2023.

[18] "A Hybrid Approach to Time Series Forecasting: Combining ARIMA and Prophet Models to Increase Forecasting Precision." Results in Engineering, ScienceDirect (Elsevier), 2025.

[19] "Comparative Machine Learning Study to Forecast Oil Production: An Example of Time Series Forecasting by ARIMA, LSTM, and Prophet." Computers & Geosciences, vol. 164, 2022, Art. 105126.

[20] "The Prophet Model Enhanced by Rigorous Cross Validation for Long-Term Solar Insolation Forecasting." Results in Engineering, ScienceDirect (Elsevier), 2025.

[21] Arslan, S. "A Novel Hybrid Methodology for Energy Consumption Forecasting Employing LSTM and Prophet Models Along With Time Series Decomposition." PeerJ Computer Science, vol. 8, 2022, e1001.

[22] "An Innovative Time Series Model Based on the Prophet Algorithm for Predicting Car Sales." IEEE Conference Proceedings, 2024.

[23] "Innovative and Cost-Effective Modular Sensors Platform for IoT and Predictive Maintenance in Industrial Settings." ScienceDirect (Elsevier), 2025.

[24] "Design of an Intelligent Sensing Device for LoRaWAN IoT Flood Alert System." Internet of Things, ScienceDirect (Elsevier), 2023.
[25] "Cost-Effective and Portable Data Collection Infrastructural Solution for IoT Indoor Environmental Sensing." Journal of Building Engineering, ScienceDirect (Elsevier), 2022.
[26] "Smart Monitoring System for Energy Consumption Utilizing ESP32 Microcontroller
[27] "Development of a Low-Cost IoT System Based on LoRaWAN for Monitoring Variables Related to Electrical Energy Consumption in Low Voltage Networks." e-Prime—Advances in Electrical Engineering, Electronics and Energy, ScienceDirect (Elsevier), 2022.
[28] "Machine Learning and IoT–Based Predictive Maintenance Approach for Industrial Applications." Ain Shams Engineering Journal, ScienceDirect (Elsevier), 2024.
[29] "Probing an Intelligent Predictive Maintenance Approach with Deep Learning and Augmented Reality for Machine Tools in "IoT-Enabled Manufacturing." Robotics and Computer-Integrated Manufacturing, ScienceDirect (Elsevier), 2022.
[30] Ayvaz, S., and Alpay, K. "Predictive Maintenance System for Production Lines in Manufacturing: A Machine Learning Approach Using IoT Data in Real-Time." Expert Systems with Applications, vol. 173, 2021, Art. 114598.
[31] Pradeep, B., et al. "Industrial IoT Predictive Maintenance Using Machine Learning Approach." Proceedings of the Third International Conference on Cognitive and Intelligent Computing, Springer, 2025.
[32] "The Experimental Application of Popular Machine Learning Algorithms on Predictive Maintenance and the Design of an IIoT-Based Condition Monitoring System." ScienceDirect (Elsevier), 2020.
[33] "General Principles of Industrial Corrosion." Elsevier Reference Module in Materials Science and Materials Engineering, 2022.
[34] Forr, O., et al. "The Effect of Bird Droppings on the Corrosion of Steel and Aluminum Used in Offshore Applications." Materials and Corrosion, vol. 74, 2023.
[35] "Economic Risk Analysis of Pitting Corrosion in Process Facilities." Journal of Loss Prevention in the Process Industries, ScienceDirect (Elsevier), 2017.
[36] Blackwell, B. F., et al. "Effect of Light Wavelength and Pulsing Frequency on the Avoidance Responses of Canada Geese." PLOS ONE, 2023.
[37] "Bird Avoidance of High Contrast Lights Tested in a Choice Test Approach: Implications for Mitigation of Human-Induced Bird Mortality." Royal Society Open Science, 2018.
[38] "A Possible Method of Protection of Birds from Danger: The Use of Lasers in Alberta Oil Sands and Elsewhere." University of Alberta, 2021.
[39] "Flickering Light for Bird Deterrence: Insights from Neurophysiology." bioRxiv preprint, 2024.
[40] "Physiology of Bird Deterrence: Flicker Vertigo and Beyond." bioRxiv preprint, 2024.
[41] Suryawanshi, V. R. "Design, Fabrication and Evaluation of a Solar Power Operated Audible Bird Repellent Device." International Journal of Scientific Research, 2015.
[42] Muminov, A., Jeon, Y. C., Na, D., Lee, C., and Jeon, H. S. "A Novel Design for Solar-Powered Bird Scaring Device." IEEE International Conference on Information
[43] Li, S., et al. "Intelligent Audio Bird Repeller for Transmission Line Tower Based on Bird Species Variation." IOP Conference Series: Materials Science and Engineering, vol. 592, 2019, Art. 012142.
[44] Yauri, R. "Development of an Electronic Bird Repellent System Using Sound Emission." Conference Proceedings, 2023.
[45] Taylor, S. J., and Letham, B. "Forecasting at Scale." The American Statistician, vol. 72, no. 1, 2018, pp. 37–45.
[46] Zonta, T., Da Costa, C. A., Da Rosa Righi, R., De Lima, M. J., Da Trindade, E. S., and Li, G. P. "Predictive Maintenance in the Industry 4.0: A Systematic Literature Review." Computers & Industrial Engineering, vol. 150, 2020, Art. 106889.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 4, July 2026
Impact Factor: 8.2

[47] Mallioris, P., Aivazidou, E., and Bechtsis, D. "Predictive Maintenance in Industry 4.0: A Systematic Multi-Sector Mapping." CIRP Journal of Manufacturing Science and Technology, vol. 50, 2024, pp. 80–103.
[48] Marino, P., Román Quintero, D. C., Santonastaso, G. F., and Greco, R. "Prototype of an IoT-Based Low-Cost Sensor Network for the Hydrological Monitoring of Landslide-Prone Areas." Sensors, vol. 23, 2023, Art

DOI: 10.48175/IJARSCT-37910