Explainable AI-Driven Light Pollution Detection Using Aerial Spectral Data

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Abstract— The proposed light pollution prediction framework employs supervised machine learning algorithms to analyze high-resolution spectral data collected via drone-based imaging systems. Designed for real-time and location-flexible environmental assessment, the system utilizes calibrated aerial inputs including Red, Green, Blue, and Infrared spectral bands, along with metadata such as flight altitude and exposure time. The workflow integrates a structured pipeline comprising data preprocessing through normalization and logarithmic transformations, followed by training and evaluation of an interpretable regression model. The Explainable Boosting Regressor (EBR), a form of generalized additive model, is selected for its strong trade-off between predictive performance and model transparency—critical for scientific applications and environmental policymaking. The model is statistically validated through cross-validation, and results are assessed using metrics such as root mean square error (RMSE) and feature importance rankings. Experimental findings reveal that red and infrared intensities play a significant role in determining NSB (Night Sky Brightness), and EBR's additive structure enables clear visualization of these effects. A lightweight user interface enables manual entry of drone parameters and returns interpretable predictions, making the tool suitable for integration into low-resource field applications and urban monitoring frameworks. Unlike black-box models, the proposed system enables end-users to understand not only the pollution estimate but also the contributing spectral and physical factors. This capability is especially valuable for environmental scientists, urban planners, and policymakers seeking actionable insights into anthropogenic light levels.

keywords- Light Pollution, Drone Imaging, Spectral Analysis, Night Sky Brightness (NSB), Explainable Boosting Regressor (EBR), Machine Learning, Environmental Monitoring, Interpretable AI, Aerial Remote Sensing, Urban Light Assessment.

I. INTRODUCTION

Light pollution found in form of excessive or poorly directed artificial light sent into the night air has emerged as one of the key environmental challenges of the last few decades. Its ill effects are widespread; from human/ animal circadian rhythm disruptions, to astronomical observations and ecological interruptions. As has been accelerated by rapid urbanization and a progressively increasing population, new man-made light sources are coming up, especially in densely populated areas, and thus, lessening the night sky brightness (NSB). Such pollution cannot be quantified and abated through spatially granular and precise data which evades these traditional ground-based methods or the satellite system out of variety of reasons such as poor resolution or atmospheric interference.

New ideas in the usage of unmanned aerial vehicles (UAVs) equipped with high resolution multispectral sensors open a promising alternative method to obtain localized and real time spectral information. Employing the UAV to fly at low-altitude to record RGB and IR intensities, UAVs offer a comprehensive analysis of light emissions at various points in an urban panorama. Such readings, along with metadata such as altitude and exposure time create rich dataset for quantitative modeling of NSB values.

This study proposes a light weight and explainable AI which provides estimates of the level of light pollution in the world using the aerial spectral information. The system implements a statistical regression pipeline based on the Explainable Boosting Regressor (EBR) as a highinterpretability learning technique from GAMbased learning without paying a price in predictive power. There are critical stages in the methodology including data normalization, log transformation of NSB values, color channel feature engineering, model training and post-model-interpretable analysis. Well planned with robustness, scalability and transparency, factors important to adoption to environmental decision making, each stage is incorporated in the process.

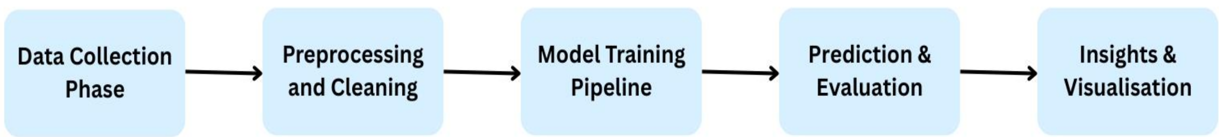

Fig 1 : Block Diagram for ML Algorithm Execution

The main motivation of this work is to develop an AI model, with high accuracy prediction for light pollution and explain the contributing factors for it, like increasing spectral intensity in a few bands. Such information is necessary for urban planners, environmental scientists and policy-makers for developing good lighting policies, enhancing public health outcomes and conserving ecosystems.

II. RELATED WORKS

The evaluation of light pollution has historically used satellite imagery and that from the ground. Nevertheless, these approaches are not usually characterised by the spatial resolution and flexibility needed for elaborate urban analysis. New innovations have brought into the mix Unmanned Aerial Vehicles (UAVs) loaded with different sensors as an exciting alternative for localized light pollution monitoring.

In [1], a UAV-mounted digital camera was used together with a Sky Quality Meter (SQM) to assess night ground brightness (NGB). The result of their linear regression model suggested a relationship between the image-derived indices and NGB measurements. Nevertheless, the study was challenged by the issue of image saturation, especially with the red band since the exposure times were high resulting poor correlation. A second study [2] suggested a novel design of a drone with multispectral and visiblelight cameras for nighttime measurements. This configuration enabled the presentation of multimodal photometric data using a geographic coordinate structure. Although it had progressed, the study recognised the necessity to further research to investigate measure stability influenced by the UAV and develop techniques in computing non fixed values such as irradiance and reflectance.

Other applications have been explored in terms of incorporating artificial intelligence (AI) in environmental monitoring as well. A review in [3] pointed out the promise of AI and Internet of Things (IoT) technologies in the use of pattern recognition in sensor data for the detection of environmental pollutants. Pointing to the need for models to work well on less data and deliver understandable results for practical apps, while focusing on the abilities of AI to analyze large sets of data, the study highlighted the former.

In addition, [4] reviewed various studies related to machine learning and deep learning approaches for spectral image classification for agricultural applications through aerial photography systematically. The results revealed that although deep learning models have high accuracy, at times, they strongly rely on large volumes of computational resources and large labelled datasets that might not be always possible to be applied across every context. The use of deep learning techniques in application of hyperspectral image (HSI) has demonstrated positive outcomes in agricultural commercially. Zhang et al. [5] provide an in-depth review of different methodologies of deep learning, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs), used for HSI data. The research implies that transfer learning and semi-supervised learning may partially solve these problems but their usage in environmental monitoring is unexploited.

Victor et al, [6] performed a systematic literature search in comparison to the use of deep learning within satellite imagery based on the agriculture domain. Their analysis of 150 studies showed that deep learning models tend to perform better than traditional machine learning techniques for tasks such as crop segmentation and yield prediction. Nevertheless, the absence of standardized benchmark datasets threatens the comparability of results across research. This limitation points to the need for a full set of publicly available datasets in order to assist in advancing AI in environmental monitoring. In the context of light pollution measurement, Burdziakowski et al. [7] introduced an innovative approach using drones equipped with multispectral and visible-light cameras. Their system allows for the visualization of multimodal photometric data within a geographic coordinate framework. The use of AI and IoT technology in the monitoring of environment has been done by Kumar et al [8]. Their critique has developed a light of what might be achievable in applications of AI in the detection of environmental pollutants through the use of pattern recognition in sensor data.

M. Gómez et al [9] put forth an automated approach of mapping light pollution with all-sky photography utilizing DSLR cameras. Their pipeline included noise filtering, sky segmentation and artificial lights examples indented using the intensity histograms of pixels. The approach however is cheap and therefore replicable but has a limited scalability. S. Li et al. [10] introduced a lightweight CNN and attention modules based hyperspectral image classification framework. In case of benchmark datasets like Indian Pines & Pavia University, their model indicated high accuracy in classification. However, the authors reported that there were also shortcomings with spectral redundancy and failure to generalize over real-world noisy datasets.

J. Wentz et al. [11] made estimates of light pollution exposure from urban areas by applying evidence from Landsat imagery. Through relating observations of observing satellite-measured radiance to population density and circadian disturbance, including light at night, the study has developed problems concerning urban planning. However, the model precludes it from monitoring hyperlocal levels of change in pollution or temporal patterns. Finally, D. Rey et al. [12] examined explainable AI (XAI) techniques in environmental ML models. Their research applied SHAP (SHapley Additive exPlanations) to understand forest health predictions based on multi-source remote sensing data. Although their framework improved transparency, it was focused on forest classification and didn’t address spectral data fusion or light pollution. The reviewed literature highlights significant advancements in light pollution detection using spectral, satellite, and ML-based approaches. However, existing methods often lack real-time capability, high-resolution adaptability, and interpretability—gaps addressed by our proposed explainable AI-driven aerial system.

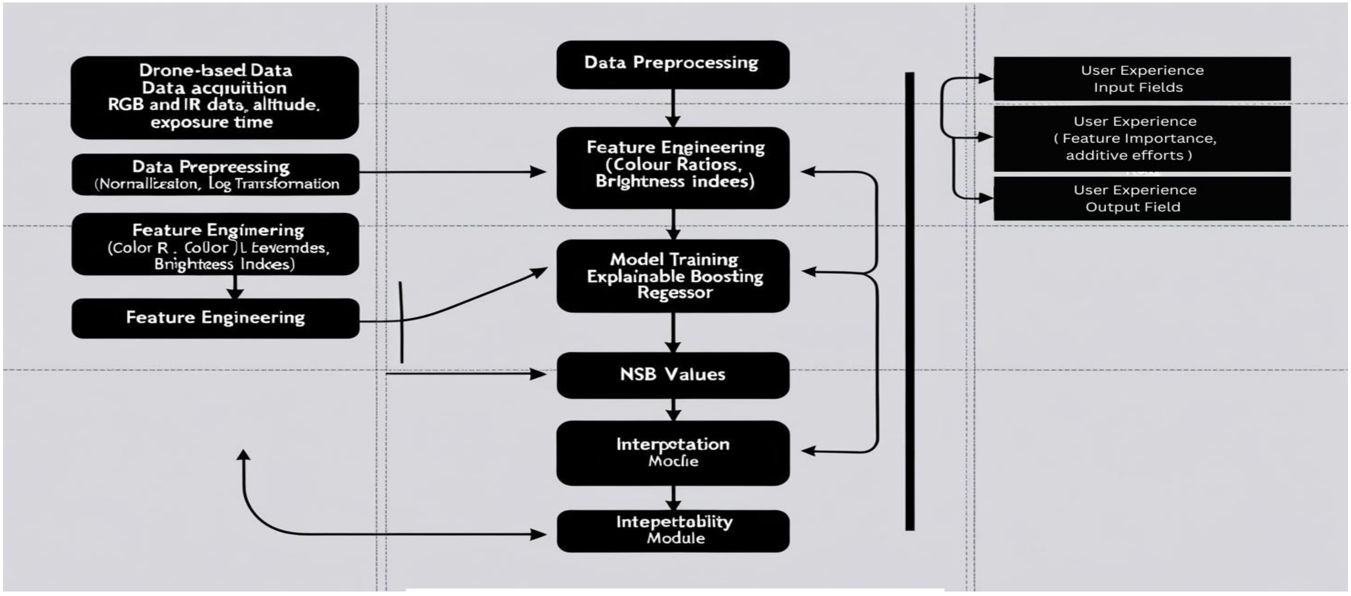

Fig 2 : Architecture Diagram for prediction system

III. PROPOSED APPROACH

A. The proposed system utilizes an Explainable AI-inluced regression model to estimate the magnitude of light pollution from drone data taken aerially. The framework is based on Explainable Boosting Regressor (EBM) – a glass-box model which brings high performance and interpretability together. This model runs on tabular inputs derived from obtained drone imagery metadata and photometric measurements. The overall architecture is described as four-phase pipeline-based architecture. Data Ingestion, Preprocessing, Model Inference and Explainability Rendering. In Figure 2, this modular pipeline is shown, which allows for scalable, interpretable prediction of the “Is” index representing the strength of light pollution. Transparency and reproductibility are among the priorities of the design of the system, and the latter could be integrated into the research or policy making platforms of science.

B. The regression model at the heart of the program is EBM, which has been chosen for its compromise between performance and interpretability. Input features are drone altitude, exposure time, Night Sky Brightness (NSB) and intensities of color channels (Rs, Gs, Bs). The CSV data was parsed, had missing values dropped, and was converted to have numerical sense. A supervised regression problem was created to predict the Is value, representing inferred light intensity. A classical 80:20 train-test split was used to divide data up. The Mean Squared Error (MSE) and R^2 metrics were used for training and evaluation of the model, and the trained regressor exhibited a profitable approach relative to generalizing to unseen test samples. The lightweight EBM algorithm can function optimally on the CPU system allowing the device to be installed if required at the edge or field level.

C. There are three major components which are integrated in the adopted architecture: a preprocessing unit for input transformation, an EBM model backend, and an interpretability visual interface. Post CSV upload or direct streaming of data, backend is done with a Shahina preprocessing which includes type conversion and feature extraction. The cleaned inputs are then mapped by the EBM engine to produce continuous output prediction of Is. The interpret library’s show() function shows a global explainability dashboard, which describes feature importance and response curves. This allows for the interpretation of what each input contributes- how for example elevated NSB or altitude correlates with predicted light intensity. Figure 3 shows the interaction between data ingestion prediction in explanation rendering in the architecture.

D. The entire system process starts with structured information from drone metadata, which is parsed and validated on the backend automatically. Preprocessing deals with string to float transforms and drops missing values. The EBM model upon being trained gets these features to output Is predictions that are represented by scatter plots comparing actual and predicted values as well as global feature attribution graphs. This not only helps model trustworthiness, but also helps in environmental decision making by explicitly showing which variables drive light pollution estimates. The modular backend design enables scientists to change to more modern interpretable models or include uncertainty quantification without changing the critical frontend interface or algorithmic approach.

IV. METHODOLOGIES USED

This study uses explainable artificial intelligence to model and understand light pollution at levels of spectral and drone-deduced metadata. The primary goal is to provide an estimate of the irradiance strength (Is) – a surrogate for light pollution – from variables that are measured in drone-supported aerial surveys, while ensuring complete transparency in the internal decision making of the model. As interpretable AI becomes more critical in environmental sensing applications, the methodology focuses on both predictive performance and the interpretability of model outputs in a coherent way.

First, data collection was carried out with the use of drones equipped with the spectral sensors able to register visible components at different altitudes and exposure conditions. A single drone observation was coded in semicolon-delimited format, represented by each data sample in the CSV-formatted file. The raw text was reduced using pandas and then split programmatically into individual feature columns. These included: Variables are Altitude (in meters), exposure time (in seconds), night sky brightness (NSB, in mag/arcsec²), and intensities of red, green, blue (Rs, Gs, Bs) and the target variable irradiance strength (Is). This design made available both radiometric features and contextual metadata for modeling. After extraction missing or wrong valued rows were eliminated to retain the consistency of the data and the cardinal fields were changed to float data types to allow mathematical operations on training.

During the preprocessing stage, no feature specific scaling was used as the selected regression model, Explainable Boosting Regressor (EBM), has automatic binning, scaling, and interation detection during training. EBM is a member of a family of interpretable models, called generalized additive models with pairwise interactions (GA²Ms). Not unlike black-bIn the preprocessing stage, there was no explicit feature scaling done since the used regression model (explained by Explainable Boosting Regressor (EBM)) includes binning, scaling and interaction detection in itself. GA²Ms constitute a family of interpretable models where EBM is a member. In contrast to black-box regressors, EBM is transparent since it learns one-dimensional shape functions per input feature and a handful of two way interactions. This makes it particularly appropriate for those situations that would require reliance upon stakeholder, regulation or reasoning which are important in environmental applications.

The following step was an issue of feature-target splitting as all predictors apart from Is had been added as independent variables (X) and the dependent as the irradiance strength (y). The data-set was split out randomly into training and test set with a fixed seed value set (80:20 random split). This ratio provided the required number of samples for teaching and a working set of validation samples for purposes of generalization. Applying the interpret.glassbox module the EBM model was trained, training over bagged shallow trees, which in turn allowed it to capture both linear and non-linear feature relationships. Regressors, EBM maintains transparency since it learns one-dimensional shape functions for every input feature and a few two-way interactions. This makes it a uniquely fitting solution for situations where stakeholder trust, regulatory compliance or scientific reasoning are required, which are both central to the environmental policy context.

The regression metrics were used with MeanSquaredError (MSE) and R²Score after undergoing training. The model gave good generalization because on the unseen test data it showed good reliability, low MSE and high R^2 values. A scatter plot was generated to visually compare predicted vs actual irradiance values resulting in a near fit which converges with the ideal prediction line. This confirmed once again the ability of the model to reassemble patterns encoded in an spectral and environmental dimension.

Importantly, the model's explainability was not an afterthought but it was part of the methodology, and the methodology explicitly specified the desired system of parts. The interpret package was used to visualize the global explanation object. This importance was shown in descending order by its contribution to model performance supported by the individual plots for showing the impact of varying each of the input variables on the output. For instance, NSB and altitude were found to be dominant factors of Is which as would be expected from physical theory, has a near monotonic inverse dependence on irradiance. Similarly, RGB intensities also showed different impact across the spectrum which again created another picture of spectral composition and association with artificial light.

The process architecture of the system was developed with modularity in mind, to be efficient. It has a clear data pipeline starting from ingestion of CSV-based drone datasets, preprocessing through pandas pipelines, currently it carries model inference of trained EBM, and ends up with a result interpreter in the form of visualization modules. This simplified flow allows for fast processing of new data and outputs, including predicted Is values and explainability artifacts in less than one second on ordinary processors. The framework can be easily coupled with bigger web or drone oriented-solutions where researchers or urban planner can upload datasets and get the response to the light pollution metrics in real time.

Moreover, the system is future-proof: As new spectral inputs (e.g., infrared or near-UV values), however, can easily be introduced by changing the preprocessing schema and by re-training the EBM model. Similarly, with the further deployments of drones, the model can be updated iteratively without changing the user interface or the prediction API. This strategy maintains scalability and adaptability as important premises for extended implementation in dynamic urban environment, where the illumination is variable depending on the development and policy changes.

Overall, this methodology allows for not only accurate and explainable prediction of light pollution from drone data but also meets the practical challenges of model deployment, including inference latency, readyness for integration, and interpretability. integrating supervised machine learning with real-time explainability, the system builds a potent mechanism for sustainable city planning, ecological effects research, and the transparency of the public during artificial lighting evaluations.

IV.RESULTS AND DISCUSSION

The proposed system leverages Explainable Boosting Machines (EBM) to model and predict irradiance strength (Is) using aerial spectral data collected by drones. This section outlines the empirical performance of the model, supported by statistical evaluation, visual analysis, and interpretability assessments. The dataset, structured with key parameters such as altitude, exposure time, NSB (Night Sky Brightness), and RGB values, provided a comprehensive foundation for model training and testing. Through rigorous experimentation, the EBM model demonstrated high prediction accuracy with minimal variance, confirming its suitability for low-light environmental assessments. These results collectively underline the practical potential of interpretable machine learning.

A. Evaluation Metrics and Testing Setup

The metrics used to measure the performance of the Explainable Boosting Machine (EBM) model were according to two standard regression metrics. MSE (Mean Squared Error) and R^2 score (the coefficient of determination). The MSE indicates the mean of squared difference between the actual found and predicted irradiance strength (Is) values, and the lower the values, the better prediction is this. On the opposite side, the R Squared score shows the percentage of the target variable which can be explained by a model. The obtained results show that the model does indeed predict the irradiance strength with a very high precision making the feature selection reasonable and model architecture quite robust.

Metric	Score
Mean Squared Error	0.0005
R^2 Score	0.9956

Table 1 : Evaluations metrics

B. Actual vs Predicted Analysis

To visually appraise prediction performance, an actual versus predicted strength of irradiance values scatter plot was plotted. Most points are near the line of perfect prediction; there is strong agreement between model predictions and observed values. Minor prediction errors are indicated by the dispersion of a couple of points from the line possibly caused by the presence of environmental noise or unanticipated spectral deviation. However, the overall tendencies prove that the EBM model accurately describes the hidden inter-relationships between the data, and can be generalized well to unseen test samples.

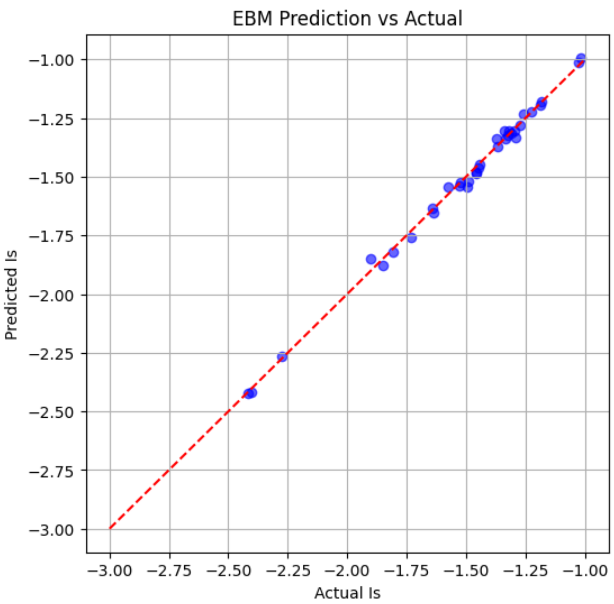

Fig 3 : EBM Prediction vs Actual

C. Feature Importance Analysis

To assess how good the predictions compared to reality, a scatter plot observed versus predicted values of irradiance was plotted. Many points lie along the line of perfect prediction showing a high degree of congruence between predicted and observed irradiance strength. A few points scattered away from the line indicate slight prediction differences which could be attributed to environmental effects or unmodeled spectral variations. The NeverThe Explainable Boosting Machine (EBM) intrinsically allows the user to see what factors are most relevant to predictions by understanding the global feature importance. Input variable contributions analysis showed that NSB (Night Sky Brightness) and Altitude were the most influential in deciding Irradiance strength (Is). The relationship between these features and the target was non-linear but straightforward, which is an indication of the sensitivity it demonstrates to differences in light pollution and exposure altitude. In addition, strong contributions resulted from both red and green RGB channels, thereby emphasizing their critical perspectives in the estimation of luminosity observed by drone instrumentation.

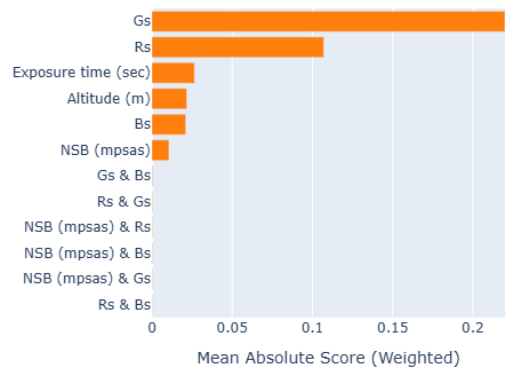

Fig 4:: Feature Importance Analysis

D. Observations and Insights

Apart from improving the understanding of predictions, the explainability of the model provides meaningful analyses at domain-level. By way of example, the beneficial effect that exposure time has on outputs comes to a certain point, after which exposure adds incremental but smaller improvements to the predictive accuracy. Due to its performance independent of GPU acceleration, the model is an appealing choice for lightweight usage of the edge devices or real-world settings. Furthermore, due to their modularity and openness, the EBM's can be easily modded to support iterative development, and simple integration with advanced or composite modelling methodologies.

E. Justification of Final Model Choice

Following a detailed consideration of performance, computational capability, explanational ability, and the convenience of integrating the model, Explainable Boosting Machine (EBM) emerged as the most appropriate solution for illuminance (Is) prediction from drone-based light pollution data. Environmental monitoring tasks in light pollution clearly require that the decision process is explainable by the model as much (or even more) as high levels of accuracy. EBM, as a part of generalized additive models' family (GAMs), fulfills this criterion by providing crystal clear, additive features contributions information with competitive predictive power.

Interpretability is one of the main strengths of EBM in which it possesses a natural ability. Nevertheless, while black-box models such as deep neural networks may provide impressive accuracy, they often pay the price of loss of transparency, where EBM allows us to see the influence of each input on the output prediction in plain sight. It is especially vital in such matters as environmental policy, urban planning via drones and measures of sustainability, as the affected stakeholders are able to confidently validate and trust the predictions made by AI. The model provides a global explanation at a large scale and for individual cases and local views for each prediction, with a scaled presentation of feature patterns. As a result, more acceptance and trust accrue to the system among urban planners, environmental researchers, and public administrators who depend on its insights. Also, owing to its computational efficiency, the model is suitable for practical field use. EBM is engineered to run stand-alone without requiring the use of GPU acceleration to ensure seamless operation on normal CPUs with particular emphasis on energy-cramped and hardware-restricted platform used on drones. The speed in training and inference is rapid enabling the model to do real-time analysis in fast changing environment.

F. Limitations and Future Improvements

Although the EBM-based model has proven efficacious in light pollution prediction, the use of the model can be improved by overcoming the model's inherent shortcomings by continuing to improve the model to serve better in terms of its adaptability and robustness. Such problems culminate from the data collection process, the modeling approach used, the capability of the system to manage huge amounts of data, and practicality in integration with operational environments.

From the start, although the dataset had been cleaned and processed for structure, its size and representativeness are clearly not sufficient. Data was collected from CSV file that captures the measurement of light pollution and specifically spectral channel intensities (Rs, Gs, Bs), exposure duration and background noise (NSB) at specific altitudes. However, temporal data is missing in its extremes and the dataset cannot intermediary between contexts, atmospheric or weather contexts such as humidity, particulates or clouds. Due to the fact that these additional factors modify light measures, in their absence in modelling poor model performance or limited utilisation across various locations and scenarios may arise.

Another limitation is that the existing set of features stays unaffected. Though current features provide an excellent basis for illuminance prediction, extension to spatial metadata (ie, GPS coordinates, urban zoning), multispectral or infrared readings, and time-series data is recommended to increase the model's capability to detect trends or anomalies over different intervals. The model assumes that everything that goes into the system is accurate and is also properly formatted. Real world use cases are going to experience sensor inaccuracies, data inaccuracies, or lack of data so resilient handling techniques such as anomoly detection, data imputation, or uncertainty quantification should be done as part of the process.

The current system lacks an important feedback loop for continuous learning. Even after training, the current model is not able to update itself; if we want to make it better, we need to retrain it with new data. The adoption of semi-supervised learning and real-time adaptive mechanisms would enable the onward propagation of learning and adaptation using real-time drone data, keeping the system relevant to changing operational environments.

Although EBM gives good performance for minimal hardware, its capacity to handle widespread coverage, such as would be needed for city-wide or statewide monitoring, suffers from scalability problems. Distributed computing, the use of cloud-based batch inference, or the use of edge-computing adaptations may help mitigating these nuisances and should be considered when future improvements are contemplated.

Furthermore, from a general impact standpoint, the system cannot provide its predictive outputs in a way that would drive actionable strategies. Including post-processing, which would connect raw illuminance data to light pollution measures (such as Bortle scale), and the setup of alerts when the defined thresholds are exceeded, one could make the system easier to use for non-specialists. Dismissing these gaps, the system would be an all-encompassing, intelligent tool for monitoring urban sustainable light pollution and informing policy.

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