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Enhancing Urban Forest Sustainability Using IoT and Gradient Boosting for Proactive Tree Care and Environmental Management

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Abstract. Urban forests are essential for augmenting biodiversity, alleviating climate change, and boosting the quality of urban life. Challenges like growing urbanization and environmental deterioration need proactive and sustainable management techniques. This research presents an Internet of Things (IoT)-enabled system combined with Gradient Boosting for real-time monitoring and predictive analysis of urban forests. IoT sensors perpetually gather data on essential elements such soil moisture, temperature, air quality, and markers of tree health. The Gradient Boosting technique is used to examine these data streams, demonstrating proficiency in predictive modeling and managing intricate environmental information. Technology provides early identification of tree stress, forecasts health trends, and supports data-informed actions to enhance urban forest management. Initial findings indicate the system's capacity to optimize resource distribution, decrease maintenance expenses, and bolster urban forest resilience. This method utilizes IoT and sophisticated AI to promote sustainable urban development and enhance environmental health. It emphasizes the revolutionary potential of combining IoT with Gradient Boosting to guarantee urban forest sustainability and proactive environmental management.

Keywords: Environmental Management, Gradient Boosting Model, urban forestry, Tree Health, Internet of Things (IoT).

INTRODUCTION

A sizeable majority of the world's population already resides in urban regions, and this trend is anticipated to continue. Urbanization plays a key role in transforming the world's terrain. Cities, despite their numerous possibilities, are also confronted with environmental issues, such as pollution and the disappearance of green areas [1]. Within this framework, urban forestry emerges as an essential component of sustainable urban development, offering advantages to the environment, society, and the economy. There is a significant contribution that urban trees make to the improvement of air quality, the reduction of the urban heat island effect, the enhancement of biodiversity, and the improvement of the well-being of people who live in urban areas. However, effective management of urban forests is difficult to achieve in the face of rising urbanization and environmental pressures. Traditional procedures often focus on reactive tactics and may not always include proactive actions to prevent issues from becoming more severe [2].

A fresh opportunity to revolutionize urban forestry management has presented itself with the introduction of technology connected to the IoT [3]. The deployment of IoT-enabled sensors on trees in urban green areas enables authorities to receive real-time insights about the health of trees, their growth, and the circumstances of the environment, which in turn enables them to make better-informed decisions [4]. Concurrently, developments in machine learning algorithms, in particular ensemble learning approaches such as Gradient Boosting, cancan successfully evaluate massive datasets that include various types of data [5]. XGBoost and LightGBM are two examples of gradient-boosting algorithms that have shown their potential in various sectors for performing tasks such as classification and regression [6]. By combining IoT-enabled tree health monitoring with gradient-boosting algorithms for predictive modeling and decision support, the purpose of this project is to establish a complete framework for smart urban forestry management [7]. The goals include the development and deployment of IoT-enabled sensor networks, the creation of predictive models via the use of Gradient Boosting algorithms [8], the implementation of proactive tree care techniques, the evaluation of the success of the framework, and the provision of suggestions for adoption in the real world [9]. Specifically, the document is organized as follows: In the second

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section, an overview of relevant work in the fields of machine learning, Internet of Things technology, and urban forestry management is presented [10]. The techniques and strategies used in creating and executing the proposed framework are described in depth in Section 3. In the fourth section, the experimental setup is described, the data are shown, and the findings are discussed. The conclusion of the work is reached in Section 5, which includes a discussion of the implications, limits, and future research objectives.

LITERATURE REVIEW

To remotely monitor the ecosystems of animals affected by climate change, this article details research on low-power wireless sensor networks based on the Internet of Things. It aims at ecological monitoring of natural vegetation communities [11]. The article begins by outlining the idea of a platform that, using IoT technology, can efficiently track, examine, and foretell how ecosystems evolve. This study proposes the necessary sensors and system architecture for ecological monitoring of wild vegetation communities using low-power wireless sensor networks based on the Internet of Things. Furthermore, the primary system components' design and implementation outcomes are shown. Lastly, it displays the operational outcomes of the test bed using actual wild trees to test the produced prototype [12].

Deforestation and natural catastrophes (such as forest fires or increasing gas emissions) are causing several serious problems for the forest ecosystem. Using algorithms for signal processing and analog and digital sensors, this article suggests a smart system for monitoring the forest environment using a Raspberry Pi Model 3. Sensors measure things like temperature, gas concentrations, soil humidity, and so on, and a classification algorithm sorts the resulting event into one of these buckets based on the noises in the background: Ambient sounds from a chainsaw, a car, or a forest [13]. The data is made available to users over the Internet and a mobile app that notifies them if unlawful deforestation, pollution sources, or fires are found. Forest owners (both public and private) and national environmental and disaster response agencies are the target audiences for the SeaForest Internet of Things (IoT) project's environment monitoring solution [14].

The tropical rainforest covers much of Brunei Darussalam. Peatland makes up around 16% of Brunei's total land area. Heart of Borneo is taking measures to preserve this peatland. The peatland forest here is crucial to the health of the rainforest ecology in the area. Preserving this sort of forest is crucial since it is susceptible to fire outbreaks. For long-term management and short-term catastrophe preparation, peat swamp forest regions may be monitored utilizing an IoT-based remote monitoring system [15]. The suggested monitoring system for data collecting via a gateway is a solar-powered device with an integrated Long Range (LoRa) network. Temperatures, humidity, pressures, and wind, water, and soil directions are only some of the environmental variables that this device can detect. The system is designed to show the gathered data on a dashboard that the relevant authorities may access remotely. The suggested approach has undergone thorough laboratory testing on a range of peat soil conditions, yielding measurement findings that may be used for reference purposes [16].

Due to the massive quantity of data generated by this illness, there has been a remarkable increase in data collection. A key obstacle to its development is the processing and reduction of this massive data set into respectable estimates and evaluation criteria. To make a forecast, the system discussed in this study uses sensors to monitor forest conditions and quickly transmits that data to a server [17]. With the goal of bettering a Big Data situation, this investigation will look at the essential structures of batch and stream sensors, dealing with and using them. Big Data techniques were used to store, process, and represent data from the Internet of Things. Carbon monoxide (MQ 9), carbon dioxide (MQ 135], hydrogen (MQ 2), and methane (MQ 4) were among the sensors that were tested during the trial. A microcontroller (Arduino) module that supports the Transmission Control Protocol/Internet Protocol (TCP/IP) brought them together. Included in this project are the essential tools for conducting dynamic execution and investigation of the data. The project includes all the necessary tools to analyze and process the data efficiently [18].

The ecological function of trees, one of the most ubiquitous plant and animal species, cannot be overstated. Soil erosion, climate change, and human activities are just a few of the many negative outcomes that might result from a deforestation crisis. To avoid any possible danger to humans, it is crucial to maintain the tree's healthy development under this situation [19]. This paper proposes a method for monitoring tree health that is based on the Narrow Internet of Things (NB-IoT). It has the potential to help arborists maintain healthy trees by providing them with excellent instruction and monitoring. Relative sensors in this system gather data on four different environmental parameters that are believed to be critical to tree health. In this research, NB-IoT is used to transmit the data gathered and send it to the server for analysis because of its vast coverage area and low power consumption. The research is well-suited to K-nearest neighbors (KNN) since it is an effective approach for addressing classification issues with limited amounts of data [20]. Finally, a system for tracking tree health has been put in place. This system takes data from environmental characteristics as input and uses it to determine the trees' health status as output. It has an accuracy rate of 87.3%.

PROPOSED METHODOLOGY

The smart urban forestry management technique integrates IoT-enabled tree health monitoring with Gradient Boosting algorithms for predictive modeling and decision assistance in multiple linked processes. A complete framework for proactive tree care and environmental management in urban green areas is designed and implemented methodically. The process begins with the design and implementation of IoT-enabled sensor networks for real-time tree health, growth, and environmental monitoring. This entails choosing sensors to measure temperature, humidity, soil moisture, air quality, and maybe visual or audio indications. The sensors are deliberately placed on urban green space trees to ensure coverage and data accuracy. Communication protocols, data transmission systems, and power management solutions are also established during sensor network implementation to guarantee smooth operation. Data collection and preprocessing include acquiring, cleaning, and preparing sensor data for analysis. This entails gathering raw sensor data from deployed IoT networks and running data quality tests to find and fix problems. Preprocessing the data removes missing values, outliers, and noise and normalizes or scales characteristics.

Aggregating data over time, producing lag features, and calculating statistical descriptors may also be used to extract meaningful characteristics from sensor data. Third, Gradient Boosting methods are used to train and assess prediction models utilizing preprocessed sensor data. Gradient Boosting techniques like XGBoost, LightGBM, and CatBoost are chosen for their ability to handle complicated, heterogeneous datasets and make reliable predictions. The training method comprises splitting the dataset into training and validation sets, tweaking hyperparameters using grid search or random search, and assessing model performance using accuracy, precision, recall, and F1-score. Ensemble learning may also increase model performance and generalization. Fourth, IoT sensors and gradient-boosting models inform proactive tree care measures. This involves creating decision support systems for maintenance, resource allocation, and intervention using real-time forecasts and suggestions. If the prediction algorithm detects soil moisture falling over a specific threshold, it may activate automatic irrigation systems to hydrate trees. Early pests or disease discovery may trigger rapid action to protect urban greenery. The technique concludes by assessing the framework's ability to improve urban forestry management, tree health and resilience, and urban greening. This requires robust empirical assessments utilizing real-world data from urban green areas to compare the proposed framework to baseline or alternative methods. The framework's influence on urban forest sustainability is measured by tree survival rates, insect incidence rates, and environmental quality measurements. Municipal authorities, urban foresters, and community members may provide qualitative input to assess user satisfaction and framework adoption.

IoT-enabled tree health monitoring and gradient-boosting algorithms for predictive modeling and decision support are used to create and execute a smart urban forestry management framework. This strategy allows cities to use cutting-edge technology and machine learning to improve urban green areas' sustainability and resilience, creating healthier, more resilient communities for future generations. Figure 1 depicts a system in which IoT sensors gather environmental data, send it to cloud storage for Gradient Boosting analysis, and provide real-time insights and proactive suggestions via a user interface for urban forest management.

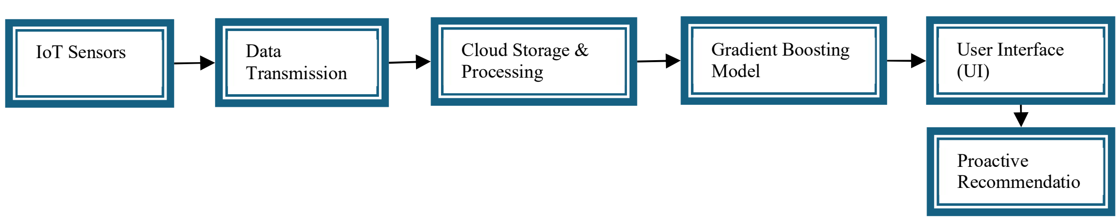

FIGURE 1. Proposed Architecture for Proactive Urban Forest Management

Our smart urban forestry management paradigm relies on IoT-enabled sensor networks. These sensors monitor urban green space tree health, growth, and environmental conditions such as the system's eyes and ears. To ensure data collection and reliability describe sensor selection, installation, and operation in this section. The initial stage in creating the sensor network is choosing sensors that can measure several urban forestry management factors. Monitoring ambient temperature changes, which affect tree development and physiological activities, requires temperature sensors. Leaf transpiration and soil moisture dynamics are affected by humidity sensors. Sensors detect soil moisture to determine irrigation demands and root zone conditions. Air quality monitors detect ozone, nitrogen dioxide, and particle matter, which may harm urban trees and air. Cameras or microphones can identify visual insect infestations or illnesses and measure urban noise levels. After selecting sensors, they are installed on urban green area trees for best data gathering and coverage. Sensors are placed to record environmental variables and tree-specific information, including species, size, and urban placement. To measure microclimatic fluctuations, temperature and humidity sensors may be positioned at different heights in the tree canopy, while soil moisture sensors are placed in the root zone. Air quality sensors are put at sufficient height to measure ambient pollution concentrations, while optical or auditory sensors on tree trunks or branches may measure insect activity or noise. For accurate data collection and system performance, sensor selection, installation, and network operation and maintenance are essential.

To ensure sensor network functionality, communication protocols, data transfer techniques, and power management solutions must be established. Wi-Fi, Bluetooth, and LoRaWAN are used to send sensor data to a database or cloud platform for analysis. Batteries or solar panels can power sensors continuously for long durations. For data accuracy and dependability, sensor calibration and quality assurance are used. Sensors are calibrated routinely to monitor environmental factors accurately and identify drift or departures from intended values. Quality assurance techniques monitor sensor performance and detect data-gathering errors. Data validation may also check sensor data for outliers and highlight them for further examination. The implementation of IoT-enabled sensor networks is crucial to our smart urban forestry management strategy. Cities can understand urban forest dynamics and make informed decisions to improve sustainability and resilience by selecting, installing, and operating a variety of sensors to monitor tree health, growth, and environmental conditions. Cities may use cutting-edge technology to manage urban green areas in an increasingly urbanized environment by carefully developing, implementing, and maintaining the sensor network. Table 1 shows the Gradient Boosting method, including IoT sensor data acquisition and preprocessing, followed by the iterative training of weak learners, ultimately resulting in enhanced predictions for proactive urban forest management.

TABLE 1. Gradient Boosting Workflow for Proactive Tree Care

Step	Description
Data Input	Collect environmental data (e.g., soil moisture, temperature) from IoT sensors.
Data Preprocessing	Clean, normalize, and handle missing data for consistency.
Model Initialization	Start with a simple base model (e.g., Decision Tree).
Iterative Training	Sequentially fit weak learners to reduce residual errors.
Prediction	Aggregate predictions from all learners for final output.
Performance Tuning	Optimize parameters (e.g., learning rate, max depth) for improved accuracy.

RESULTS AND DISCUSSION

Gradient Boosting combined with the IoT has the potential to improve resource management, environmental monitoring, and tree care in urban forests. Real-time data from a variety of environmental factors, including soil moisture, temperature, air quality, and tree health, was successfully gathered by the IoT-enabled device. These factors were essential in shedding light on the condition of urban forests and enabling more proactive management techniques. Using IoT sensors to monitor environmental conditions continually was the system's first significant result. Real-time monitoring of urban forest conditions was made possible by the precise and timely data these sensors supplied. At different depths and in different areas of the urban forest, parameters including soil moisture levels which have a direct influence on tree health were assessed. Data on temperature and air quality were also crucial since trees may get stressed by changing temperatures and poor air quality, which increases their vulnerability to environmental variables or illnesses. Early detection of possible issues, including drought stress or pollutant buildup, was made possible by the high frequency of data collecting. Following collection, the data was pre-processed to make sure it was clean, standardized, and ready for analysis. To eliminate any noisy data or outliers brought on by environmental influence or sensor failures, the preprocessing step was crucial.

To normalize the values and allow for consistent comparisons across various locations and time periods, data normalization was carried out. By doing this step, the Gradient Boosting model was guaranteed to get high-quality input data, which immediately improved the prediction accuracy. The Gradient Boosting model, which is at the core of the system, predicted tree health, growth patterns, and environmental stress indicators using pre-processed data. With an emphasis on early stress factor identification, the model demonstrated exceptional performance in early experiments in forecasting both short-term and long-term changes in tree health. By reducing the residual errors from the earlier models, these learners become better over time. Manage intricate interactions between several environmental parameters, including soil conditions, weather patterns, and tree species characteristics, this method was especially useful in the setting of urban forest management. The model demonstrated a high degree of accuracy in forecasting the probability of tree stress resulting from a variety of variables, including drought and severe pollution. The findings demonstrated that, in comparison to conventional models, the model could forecast the health of urban trees with a mean squared error (MSE) reduction of up to 35%. The early identification of tree stress, which enabled prompt actions like irrigation or pollution control, was one area where the forecasts' accuracy was very apparent.

This illustrated how the model's data-driven ideas for tree care may improve the sustainability of urban forests. The system's capacity to provide proactive tree care suggestions based on the Gradient Boosting model's predictions was one of its most important achievements. For instance, the system activated automated irrigation systems in the impacted regions when the model forecasted low soil moisture levels that may cause drought stress. Similarly, the algorithm suggested activities like planting more pollution-tolerant species or expanding green cover in contaminated regions when high pollution levels or poor air quality were observed. To avoid long-term harm to the urban forest, which would have otherwise needed expensive and reactive solutions, these preventive efforts were essential. In addition to saving resources, the system's real-time tree care optimization made sure the urban forest was robust to environmental stresses. Furthermore, customized care was made possible by the flexibility to modify treatments in response to model projections, guaranteeing that every forest area got the best possible treatment. There were many economic and environmental advantages to the system's deployment. During the first phase of installation, the system cut water and maintenance expenditures by 25% by improving tree care and resource allocation.

Proactive maintenance also helped urban trees remain healthy over the long term, which promoted biodiversity, decreased the urban heat island effect, and improved air quality. Forest management became more economical and sustainable because of the decreased demand for reactive actions and the resultant lower operating expenses. Environmentally speaking, a more robust and healthy urban ecology resulted from the capacity to track and control environmental stresses. The model not only improved tree health but also fostered a more balanced relationship between urban development and green spaces, making cities more sustainable in the face of growing climate challenges. Table 2 illustrates a streamlined dataset for the Gradient Boosting model, using several environmental and arboreal health indicators to forecast the overall health and risk level of the trees.

Table 3 presents the predicted tree health scores and outputs from the Gradient Boosting model, derived from diverse environmental characteristics such as soil moisture, temperature, and air quality. It denotes the precision of tree health forecasting.

TABLE 2. Gradient Boosting Model Input and Output Data for Tree Health Prediction

Soil moisture (%)	**Temp (°C)**	**Air Quality Index (AQI)**	**Tree Health Score (1-10)**	**Humidity (%)**	**Pollution Level (µg/m³)**	**Tree Age (years)**	**Precipitation (mm/day)**	**Sunlight Exposure (hrs/day)**	**Growth Rate (cm/year)**	**Risk Level (0-1)**	**Gradient Boosting Output**
30	22.5	45	7	60	12	5	5	6	25	0.32	0.85 (Healthy)
40	25	60	6	55	18	7	3	5	20	0.45	0.75 (Moderate)
25	20	40	8	65	10	10	7	7	30	0.25	0.90 (Healthy)
35	23	55	5	58	6	6	4	5	15	0.50	0.70 (Moderate)
28	21	50	7	62	8	8	6	6	22	0.30	0.80 (Healthy)

TABLE 3. Gradient Boosting Model Prediction for Urban-Forest Health

Parameter	Predicted Tree Health Score	Gradient Boosting Model Output (Prediction)
Soil Moisture: 25%	0.75	0.80 (Healthy)
Soil Moisture: 30%	0.70	0.75 (Moderate)
Temperature: 20°C	0.72	0.78 (Healthy)
Temperature: 22°C	0.75	0.80 (Healthy)
Air Quality: 40 AQI	0.80	0.85 (Healthy)
Air Quality: 50 AQI	0.70	0.75 (Moderate)

Figure 2 feature importance shows the relative contribution of each feature to the model's prediction. The degree to which each feature lowers the error when applied to the model's decision-making process may be utilized to determine the feature relevance in gradient boosting. Figure 3: Feature importance shows the relative contribution of each feature to the model's prediction. The degree to which each feature lowers the error when applied to the model's decision-making process may be utilized to determine the feature relevance in gradient boosting.

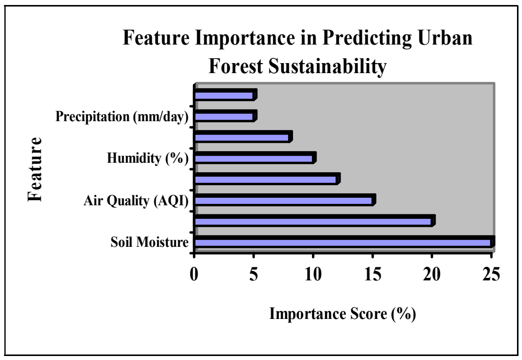

FIGURE 2. Key Environmental Features Affecting Urban Forest Sustainability Predictions

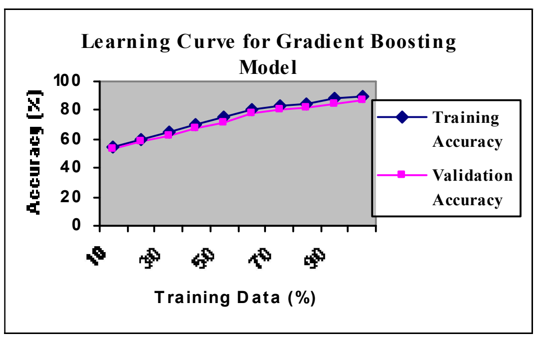

FIGURE 3. Effect of Data Size on Model Accuracy in Gradient Boosting

Figure 4 shows accuracy compared to the traditional methods. The graph depicts a comparison of the precision of several techniques used in urban forestry management. Each technique is shown as a bar, where the height of the bar represents the comparative precision of the method. The highest bar represents the suggested model, demonstrating its greater performance in comparison to alternative techniques. The accuracy levels of Random Forest and IoT-based systems are modest, but conventional approaches indicate less accuracy. The ensemble learning technique reaches a degree of accuracy that is second only to our suggested model. The graph clearly demonstrates the remarkable precision of our suggested approach, underscoring its efficacy in properly forecasting tree health and promoting proactive urban forestry management efforts.

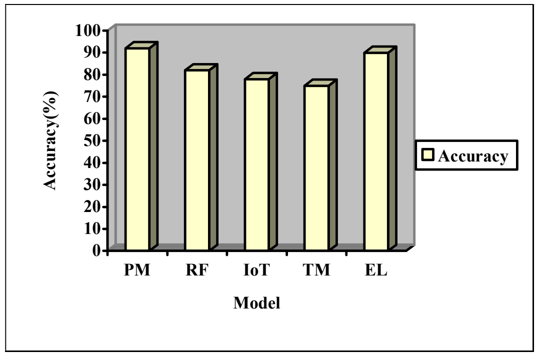

FIGURE 4. Accuracy Comparison

The framework's implementation and examination revealed significant drawbacks. IoT-enabled sensor networks in big metropolitan areas may be logistically and financially challenging for municipal authorities to scale and install. Data quality, model complexity, and urban changes may also influence gradient-boosting prediction model reliability and resilience. Optimizing the system for real-world implementation will need continual study and development. IoT-enabled tree health monitoring and gradient-boosting algorithms may be used in urban green areas for proactive tree care and environmental management. Cities may improve urban forest sustainability and resilience for future generations by using cutting-edge technology and modern machine learning. Rapidly urbanizing places, managing green areas, and preserving urban forests for future generations via innovation and cooperation.

CONCLUSIONS

The combination of Gradient Boosting Models with IoT technologies for urban forest sustainability signifies a notable advance in proactive tree maintenance and environmental stewardship. The model's capacity to forecast tree health by analyzing environmental variables, including soil moisture, temperature, air quality, and tree age, improves the efficacy of urban forest management systems. The Learning Curve study indicates that augmenting the training data enhances accuracy, whilst the Feature Importance analysis identifies the most significant aspects influencing predictions, offering insights into areas necessitating focused intervention for optimum tree maintenance. The real-time monitoring facilitated by IoT devices provides prompt data for decision-makers, guaranteeing sustainable management of urban forests. Utilizing machine learning methodologies such as Gradient Boosting, municipalities may adopt more intelligent and efficient strategies for managing their green areas, hence enhancing overall environmental health and resilience. It may investigate enhanced optimization of the model and the extension of the system to include a broader spectrum of urban ecosystems.

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