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Intelligent Streetlight Control System Using Machine Learning Algorithms for Enhanced Energy Optimization in Smart Cities

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Abstract

In the USA, where large-scale city infrastructure uses huge amounts of energy, street lighting collectively makes up a large percentage of city-wide electricity consumption. As cities become smarter and greener, there is an immediate demand to update the management of public lighting networks. This research's prime objective was to create an adaptive machine learning system for streetlight control that can react automatically to the environment and human activity patterns in real time. The development of our intelligent streetlight control system led us to build a complete dataset that contains the necessary elements for context-based lighting decisions. The dataset contains contemporary, along with historical readings of ambient light intensity expressed in lux units, which delivers an essential understanding of natural illumination and lighting needs. The primary performance metric is accuracy, which indicates the number of accurately predicted instances against the number of overall predictions. Furthermore, a Confusion Matrix is utilized to present an in-depth breakdown of the outcomes of classification, illustrating the number of examples that were accurately or inaccurately classified into each class. The application of an intelligent streetlight system using machine learning is directly in line with the strategic policies of the U.S. Department of Energy (DOE), specifically its requirements regarding the modernization of the smart grid, energy efficiency, and carbon reduction. By providing real-time data-driven control of street lighting in response to environmental and usage conditions, the system makes full integration of municipal infrastructure into the smart grid possible. At the policy level, the system is an effective and pragmatic tool for municipalities looking to achieve federal and local climate action targets. Greenhouse gas (GHG) mitigation is achieved through the reduction of electricity consumption through adaptive lighting, and the machine learning function minimizes human interaction, maximizing operational autonomy and cost savings. One of the strongest ramifications of using the intelligent streetlight system is the possibility of huge cost reductions on city utility budgets.

Keywords: *Smart City, Machine Learning, Intelligent Streetlight Control, Energy Optimization, Adaptive Lighting, Environmental Sensing, Public Safety, Urban Infrastructure, Sustainability, Traffic Analysis.*

Introduction

Urban areas in the United States are increasingly looking to cut energy consumption, decrease operating expenses, and reduce environmental impact. One of the largest contributors to citywide energy consumption is street lighting, which, in many municipalities, makes up almost 40% of municipal electricity consumption (Asif et. al., 2022). Traditionally, street lighting has been controlled using primitive control methodologies, including fixed scheduling or rudimentary ambient light sensing, which do not take into consideration the nuances of metropolitan life. The legacy models tend to lead to wasteful energy consumption by lighting up areas during low-activity times or suboptimal safety by under-illumination critical zones at critical hours. In the context of new smart city paradigms, where data-driven decision-making is paramount, intelligent streetlighting is an attractive area to innovate (Ahmed et al.,2025).

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According to Anonna et al. (2023), the advances in machine learning and edge computing technologies provide an opportunity to overhaul streetlight infrastructure using real-time intelligence and flexibility. As IoT-based sensors proliferate, cities can gather an extensive range of contextual information, from traffic volume and pedestrian flow to meteorological conditions. By processing it through machine learning models, the data can provide predictive models that accurately predict lighting requirements. Barua et al. (2025), highlighted that these kinds of systems can adjust brightness, turn lights on and off, and even synchronize with neighboring infrastructure elements such as traffic signals or emergency services. By transitioning to an intelligent lighting network, cities can save energy as well as become operationally efficient and increase the overall quality of life.

Problem Statement

Even with technological progress, Chowdhury (2024), underscored that most municipalities in the U.S. still employ legacy street lighting infrastructures that are not dynamic or context-aware. These traditional street lighting infrastructures, normally controlled using fixed timers or binary sensor data, are crude at best in trying to address the dynamic nature of the city. For example, a timer-driven system may light an entire highway for hours when there is no traffic, and sensor-based models may be activated by false positives or miss slow-moving crowds or transient blockages. Consequently, these infrastructures end up wasting energy or shortage illumination when it is needed, which compromises not just sustainability but also safety (Chouksey et al., 2025).

Additionally, the static design of legacy control systems does not facilitate adaptation to seasonality, special traffic patterns, or emergency responses, resulting in inefficiencies and unsafe conditions. Integration with other city systems is also not possible, and as such, no integrated response can be made to city-wide events (Gazi et al., 2025). In an information-intensive period, not leveraging the insights gained by machine learning is equivalent to forgoing major energy savings and system improvements. As per Hossain et al. (2025b), the lack of intelligent and adaptive streetlight systems not only places undue burdens on municipal budgets but also hampers the move towards greener and more resilient city infrastructures. This is why there is an urgent need for intelligent, learning-based streetlight management.

Research Objective

The prime objective for this research team focuses on creating an adaptive machine learning system for streetlight control, which can react automatically to the environment and human activity patterns in real time. Unlike traditional systems with schedule-based or binary motion detection, the new system will use combined sensor data from ambient detectors and weather stations, together with traffic cameras along occupancy sensors to develop a full operational understanding. Multiple machine learning algorithms trained on multi-purpose data will forecast suitable lighting conditions for each operational situation including busy traffic periods and night zones and weather situations with reduced visibility. Through continuous model learning the system builds increased decision accuracy over time while adjusting its conduct following modifications in seasonal patterns or improvements of infrastructure or public events.

The system architecture uses modular construction methods alongside scalability features which work together with edge computing technology for fast decisions cloud-based data analysis and future trend evaluations. A distributed system combines rapid response capabilities with powerful data analytical functions because of its design. Machine learning algorithms enable the system to reveal elaborate patterns between the combined factors of fog lighting needs alongside speed and pedestrian populations which standard rule-based systems cannot discover. The main goal exists to create intelligent lighting technology which adjusts to city movement patterns to minimize power usage without reducing public facility safety or functionality.

Significance of the Study

Yang et al. (2020) contended that there are two main benefits to using machine learning hardware in streetlight control systems: they create powerful urban energy management tools for advancing the

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development of sustainable smart cities. The operation of smart cities depends on energy efficiency, as street lighting remains one of the fundamental areas to focus on for improvement. Municipalities that limit excessive lighting while matching illumination to current usage needs will save substantial energy, which enables city services and lowers organizational carbon emissions. These systems eliminate the need for human presence in maintenance processes by performing autonomous self-checks that identify bulb failures and detect unnatural system usage, which enables both efficient machine operations and decreased maintenance expenses. The proposed system generates profitable returns by reducing electricity bills and maintenance expenses, which will lead to financial returns in fewer than three years.

According to Wu et al. (2021), when streetlights function using intelligent control, they generate multiple benefits, but they also establish widespread effects on public safety, together with urban standards of living. Street illumination at proper levels creates conditions that decrease traffic accidents while discouraging crime and making spaces safer for pedestrians along cyclists. Real-time operational adjustments in lighting control produce spaces that brighten only in response to activity while maintaining safety standards for dark areas, but minimizing power consumption. Zulfizar (2023) posited that these integrated systems enable data interchange between smart city platforms that include information delivery to emergency units as well as traffic control entities and urban development authorities. The integrated system improves understanding of current situations throughout different city services, which results in a better-connected city infrastructure. This initiative serves simultaneous tactical operational purposes and strategic purposes to make cities pioneers in advanced infrastructure development.

Literature Review

Conventional Streetlight Systems

Guo et al. (2019), reported that streetlight control systems in the traditional sense have long depended on basic motion detection or simple time-based solutions to regulate street lighting. These take on fixed schedules and turn the lights on at the onset of dusk and off at dawn according to pre-set astronomical timers or light-sensitive sensors. Although easy to set, these do not take into consideration dynamic real-world conditions such as variations in traffic flow, weather disturbances, or emergency conditions. Moreover, motion-sensor-driven systems, activated by motion, are prone to false positives (such as small animals or environmental noise) or detection latency, which provide ineffective lighting at critical times. These shortfalls render these traditional systems rigid and reactive and do not provide much space for proactive energy management or adaptive response through the use of predictive analytics (Hossain et al., 2025c).

In addition, these legacy systems are unable to distinguish between different zones of activity or react to changing trends in metropolitan behavior. For example, the difference between an area and the actual presence of people or traffic is not accounted for by the use of a time-based system, resulting in enormous wastage of energy. Even motion sensors are mostly reliable in very close range and are unlikely to cover slowly moving or long-range entities at all, further reducing the efficiency of operation (Joo et al., 2020). Maintenance is also an area of concern as the legacy system does not provide diagnostic feedback, forcing municipalities to rely on physical inspections or citizen reports to detect faults. As cities become denser and more interconnected, the shortcomings of these systems become all the more apparent, and there is an urgent need to switch to intelligent data-driven lighting management (Mir et al., 2024).

Smart City Infrastructure and IoT Integration

Maheshwari et al. (2021), posited that the introduction of smart city programs has led to the establishment of a new phase of city infrastructure, distinguished by large-scale Internet of Things (IoT) device deployments and data-driven decision-making models. The street lighting system has become an essential application domain in the context of digital transformation. IoT--=reetlights can be fitted with a range of sensors—like motion detectors, air quality sensors, thermal sensors, and surveillance cameras—to form an extensive and networked data environment. These sensors provide instantaneous data input, and the city administrators can oversee environmental conditions, energy consumption, and adjust system performance

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in real-time. By integrating with artificial intelligence (AI) and machine learning (ML) technologies, these devices can switch from the reactive to the predictive mode of operation, enabling them to provide smarter in-line control that is synchronized with actual city usage (Langa & Mathaba, 2024).

AI and ML are key to reshaping legacy energy infrastructures through the ability to analyze large quantities of sensor data, detect patterns, and make informed decisions independently. For instance, an AI-enabled intelligent streetlight might detect traffic density at specific times of day or pedestrian traffic at the approach of events in the area and adjust the lighting. Beyond on-off switching, ML-based algorithms provide the ability to continually optimize system performance through adaptive learning, and so are superior to rigid rule-based alternatives (Mir et al., 2024). As part of an overall smart grid framework, intelligent streetlighting also provides the ability to manage the demand side of energy consumption, enabling the utility to better manage the delivery of energy to the urban landscape. These features not only lend themselves to municipal sustainability but also provide the basis for integrated urban environments where elements of the infrastructure inform and react to each other in real time (Maheshwari et al., 2021).

Machine Learning in Energy Optimization

There is extensive literature on the use of machine learning techniques to optimize energy consumption in street lighting and other applications. The most widely used methodologies are decision trees, neural networks, and fuzzy logic models. Decision tree models are utilized to predict lighting requirements as input features, including the hour of the day, weather conditions, and traffic density, enabling unambiguous, rule-based decisions based on historical data (Mouaadh et al., 2022). Although effective, yet simple to implement and understand, decision trees tend to be ineffective in addressing sophisticated, non-linear relationships found in the real-world environment. In response to addressing these challenging interactions, the use of neural networks—most notably deep learning architecture—has been proposed to abstract these complicated interactions. By learning from large data quantities, the network can detect implicit patterns and achieve high-accuracy decisions of when and how streetlights are turned on (Nagamani et al., 2019).

In other work, rule-based automation has also been achieved through the use of fuzzy logic controllers, in which pre-defined linguistic rules ("if low visibility and high pedestrian traffic, then increase brightness") drive lighting decisions. While these systems are more flexible than hard-wired logic, they are still domain-dependent and do not adapt to changing conditions unless reprogrammed (Palmer & Gibbons, 2021). Hybrid techniques that integrate the employment of several machine learning (ML) techniques also hold promise to enhance energy efficiency, such as the combination of using genetic algorithms to evolve feature selections and support vector machines to predict the future. These previous attempts attest to the potential of ML to enhance streetlight performance but also reveal limitations, the primary one being real-time adaptability and context awareness. The majority of implementations to date are narrow in scope and depend on static feature sets or localized sensor input, which limits their applicability in dynamic cityscapes (Putrada et al., 2022).

Research Gap

Reza et al. (2025), argued that even with the growth in machine learning and IoT integration, the area of multi-feature, context-aware streetlight infrastructures that can adjust in real-time to the conditions of the city is still vastly understudied. The existing solutions are centered around standalone variables—motion detection, for instance, or the time of day—without considering the interaction between various variables such as pedestrian traffic, automotive traffic flow, environmental conditions, and event-induced anomalies. In addition, most ML-based deployments utilize offline learning techniques but cannot learn incrementally, and the system does not continuously learn and adapt as the patterns within the city change. This static approach suppresses the full potential of intelligent lighting and does not take full advantage of the data-intensive environments created using contemporary sensor networks (Rajat et al., 2021).

Shovon et al. (2025) asserted that Missing is an end-to-end adaptive system that merges various sensor data as well as contextual factors into an integrated, learning-enabled model able to produce intelligent lighting decisions in real time. It would not just optimize energy consumption but also dynamically adapt to provide

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public safety as well as contribute to improved user experience. For instance, it may determine whether an abrupt change in the weather demands greater visibility or whether an emergency vehicle requires an illuminated path. Moreover, most existing research does not incorporate edge computing integration, which is essential for the provision of low-latency responses on distributed urban infrastructures. Filling the gap demands an end-to-end, real-time, and decentralized system that continually optimizes its action through feedback loops, enabling the new standard in intelligent public lighting for smart cities (Sumon et al., 2024).

Data Collection and Preprocessing

Data Description

The development of our intelligent streetlight control system led us to build a complete dataset that contains the necessary elements for context-based lighting decisions. The dataset contains contemporary along with historical readings of ambient light intensity expressed in lux units, which delivers an essential understanding of natural illumination and lighting needs. Time sequence spans hourly segments, which the system groups into peak traffic times, off hours, and transitional times to represent normal urban movement rhythms. The pedestrian count derives from motion sensors along with smart surveillance to show dynamic traffic density levels throughout different zones. The model obtains current weather specifications through local meteorological APIs, which incorporate cloud cover patterns and precipitation among other variables affecting lighting requirements. The system tracks kilowatt-hour energy usage per lighting unit to understand consumption patterns as well as evaluate control strategy efficiency. Multiple significant characteristics build the fundamental structure of the machine learning model, which allows it to deliver smart lighting solutions that correspond with actual urban environments.

Preprocessing Steps

The provided preprocessing code script followed an organized and comprehensive pipeline for reading the dataset for use with machine learning models. Cleaning null values is tackled at the outset, where numerical column null values are replaced with the median, and categorical variables are replaced with the mode to prevent loss of data through null values. The pipeline then scales and transforms features using a standard scaler to normalize numerical data to zero mean and unit variance, which is critical for magnitude-sensitive algorithms. Temporal features are also derived from the Timestamp column, including the hour of day, weekday, and binary day/night feature, which offers meaningful context to model lighting requirements. Although the given script has good preprocessing and engineering practices, there is no use of Principal Component Analysis (PCA) to reduce the feature space into dimensions, remove multicollinearity, and increase model efficiency by converting data into principal components carrying most of the variance. Adding PCA to future versions of the script would further streamline model training and possibly decrease computational load without an appreciable loss of information.

Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is an essential step in the data science cycle during which datasets are explored graphically and statistically to find the underlying patterns, identify anomalies, check assumptions, and gauge data quality before the construction of predictive models. The main function of EDA is to gain an intuitive sense of the data's overall structure and relationships using summary statistics, correlation matrices, and visual diagrams such as histograms, boxplots, scatterplots, and heatmaps. Through the application of EDA, data scientists can identify outliers, check for missing and inconsistent values, and estimate feature distributions, which informs data preprocessing techniques such as normalization, transformation, or encoding. Moreover, EDA provides insights into feature relevance and interactions that can influence the feature engineering and choice of model. In the case of machine learning for streetlight intelligence, EDA would verify the hypotheses, like whether energy consumption aligns with pedestrian traffic or weather conditions, ultimately leading to better and context-aware models.

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Average Hourly Energy Consumption

The implemented Python code analysis employs pandas and seaborn libraries to work with and present hourly energy consumption data. The script first transforms 'Timestamp' data to date-time objects from which it extracts features for 'Hour' and 'Weekday', plus 'Month'. A new binary feature called 'Is_Peak_Hour' is created through an evaluation of 'Hour' values that exist either between 7-9 am and 5-10 pm. The program displays the average 'Energy Consumption (kWh)' values for every hour through a line plot where peak hours receive unique line coloring to simplify understanding of daily energy consumption patterns.

Output:

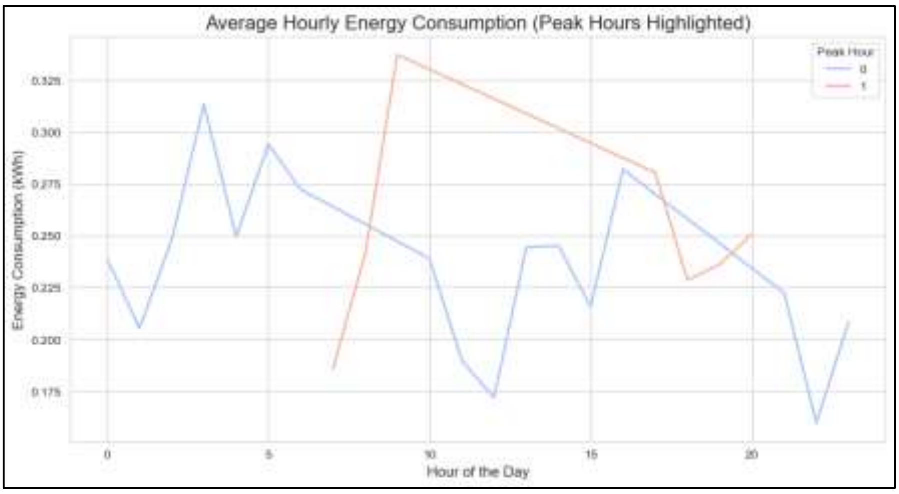

Figure 1: Average Hourly Energy Consumption

The chart above shows graphically the variation in energy consumption in the unit kilowatt-hour (kWh) during the day, with the peak hours indicated. The x-axis shows the hour of the day (from 0 to 23) and the y-axis shows the average consumption. A clear difference between non-peak (orange line) and peak (blue line) hours is shown. We can see that the non-peak hours are much higher during the day's peak hours, specifically between 8 AM and 1 PM, where the peak is slightly higher than 0.325 kWh. The non-peak hours, on the other hand, are more unpredictable and feature lower energy consumption, notably late at night and very early in the morning (e.g., at around 7 AM and beyond 9 PM). This is clear evidence of how the demand for lighting follows the rhythm of the city's activities, which are at their highest during the daytime operating hours. The chart is an important product of Exploratory Data Analysis (EDA) since not only does it affirm existing presumptions that the energy demand spikes, but also shows the potential to specifically target optimization through the use of intelligent controls at certain times of the day.

Visualizes Traffic Count vs. Traffic Density

The computed code was implemented using the matplotlib and seaborn packages to generate the heatmap plot. It first initializes the figure with the desired dimensions and then reshapes the data using the pivot_table function of the panda's library. The reshaped data is stored in the heatmap_data variable, and its index is set to 'Traffic Count' and column to 'Traffic Density', with the values as the mean of 'Dim Level'. The sns. The heatmap function is then called to produce the heatmap, which shows the mean 'Dim Level' for various combinations of 'Traffic Count' and 'Traffic Density', using the 'YlGnBu' color map and the color bar labeled as 'Dim Level'. Lastly, the title and axis names for the plot are set, and the plot is shown.

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Output:

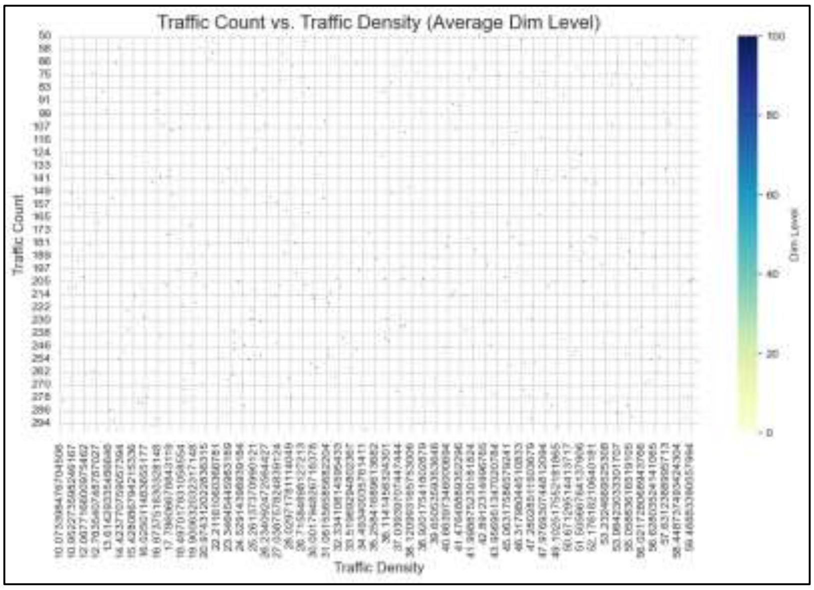

Figure 2: Visualizes Traffic Count vs. Traffic Density

The above chart examines the interaction between streetlight dimming response and real-world traffic activity within an intelligent lighting system. Traffic density and traffic volume, both key indicators of the use of the street, are represented along the x-axis and y-axis, respectively. The color scale, from light yellow through darker blue, indicates the dim level of the streetlights on an average basis, wherein darker values indicate greater illumination (lesser dimming). Although the overall scatter of points seems loose and sparse, implying much variability within the data, one can notice that higher traffic density and volume areas tend to be accompanied by greater dim levels, as evidenced by the darker blues found in the upper right. This trend is consistent with the desired adaptive response of intelligent lighting—greater traffic necessitating brighter lighting for safety, and lower traffic enabling greater dimming and energy savings. These types of insights gleaned through visual examination are invaluable to the validation of model hypotheses and the tuning of system response to actual usage characteristics.

Energy Consumption by Weather Condition

The computed code script uses matplotlib and seaborn libraries within Python programming while showing how 'Weather' conditions relate to 'Energy Consumption (kWh)'. Sns. Boxplot produces the box plot inside a specified figure through which it depicts 'Energy Consumption (kWh)' on the y-axis against 'Weather' on the x-axis while using colors from the 'Set2' palette. The plot gets its title set to 'Energy Consumption by Weather Condition' while the x-axis receives 'Weather' labels and the y-axis gets 'Energy Consumption (kWh)' names and the x-axis label rotation reaches 45 degrees for clear visual understanding. The presentation of the plotted box plot is executed through plt.show().

Output:

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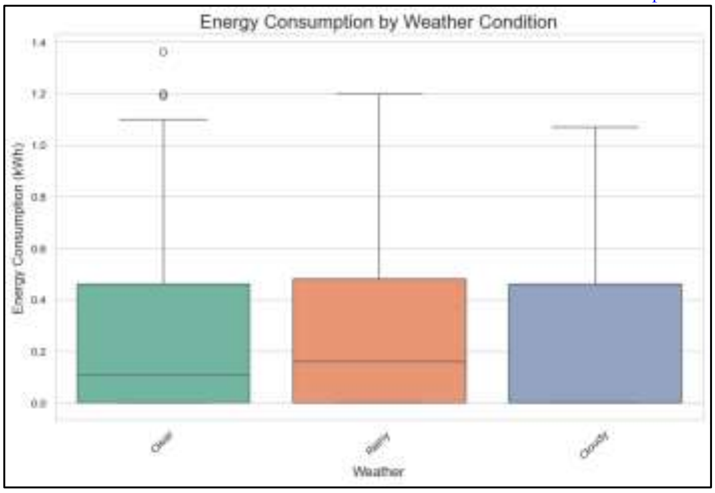

Figure 3: Energy Consumption by Weather Condition

The box plot above shows energy consumption measurement (in kWh) under Clear, Rainy, and Cloudy conditions. The middle range of energy consumption stands at 0.2 kWh throughout the three weather condition groups. The interquartile range (which measures box height) indicates that bigger variations in energy usage happen under Rainy and Cloudy conditions than under Clear conditions. The Clear weather condition contains several exceptional cases that show higher energy consumption reaching 1.35 kWh, but no such events occur in either Rainy or Cloudy data points. Both Rainy and Cloudy conditions reached a maximum energy usage of 1.2 kWh, yet all types of weather showed minimal usage of 0 kWh.

Traffic Count and Energy Consumption

The geographic scatter map was crafted through a Python implementation that depends on the plot. Express library. Through scatter_mapbox the code requires a DataFrame (df) that contains 'Latitude' and 'Longitude' columns to define mapping coordinates. The map points get their colors from the 'Energy Consumption (kWh)' data points while their sizes relate directly to the 'Traffic Count'. Viewing points with a mouse cursor triggers the display of Street ID and Dim Level information. The traffic count and energy consumption map utilizes the 'carto-positron' Mapbox style at a zoom level of 12 and displays the information through its title 'Traffic Count and Energy Consumption Map'. Finally to display the interactive map the program uses fig.show() after removing margins on all sides of the layout.

Output:

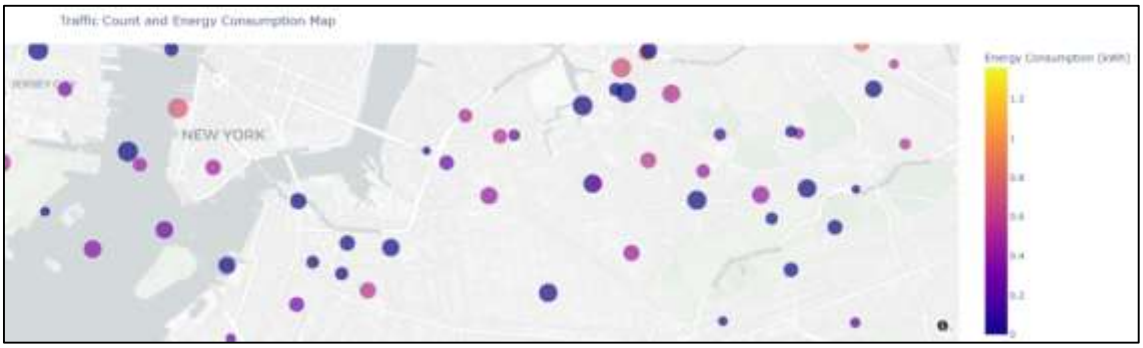

Figure 4: Traffic Count and Energy Consumption

The above geographic scatter map shows traffic count and energy consumption data points for multiple locations which seem to represent the New York City metropolitan area. The visual representation utilizes a circle size to display traffic activity whereas the spectrum from dark purple to yellow indicates energy

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usage in kilowatt-hours with yellow circles indicating elevated energy consumption. The majority of locations present higher energy consumption patterns along with their greater traffic statistics based on the size and color representations. The data reveals locations where traffic amounts differ from the amount of energy drawn independently of each other. The spatial mapping allows a better understanding of these variables to identify locations where traffic congestion and energy usage simultaneously rise and areas demonstrating alternative factor combinations.

Dim Level Adjustment Over Traffic Density

The Python script makes use of the matplotlib and seaborn libraries to plot a scatter plot illustrating the interaction between 'Traffic Density' and 'Dim Level', differentiated further by 'Day/Night' and the magnitude of 'Traffic Count'. It starts by creating a figure with the desired dimensions and then makes use of sns. Scatterplot to generate the plot, setting the x-axis to 'Traffic Density' and the y-axis to 'Dim Level'. The 'hue' attribute uses 'Day' or 'Night' to color the points and the 'size' of the points as determined by the 'Traffic Count', with the desired scale for the sizes and alpha for transparency. The script then makes the title of the plot 'Dim Level Adjustment Over Traffic Density (Day vs. Night)', makes the x-axis 'Traffic Density' and the y-axis 'Dim Level', and inserts a legend to differentiate between 'Day' and 'Night'. Lastly, plt.show() shows the resultant scatter plot.

Output:

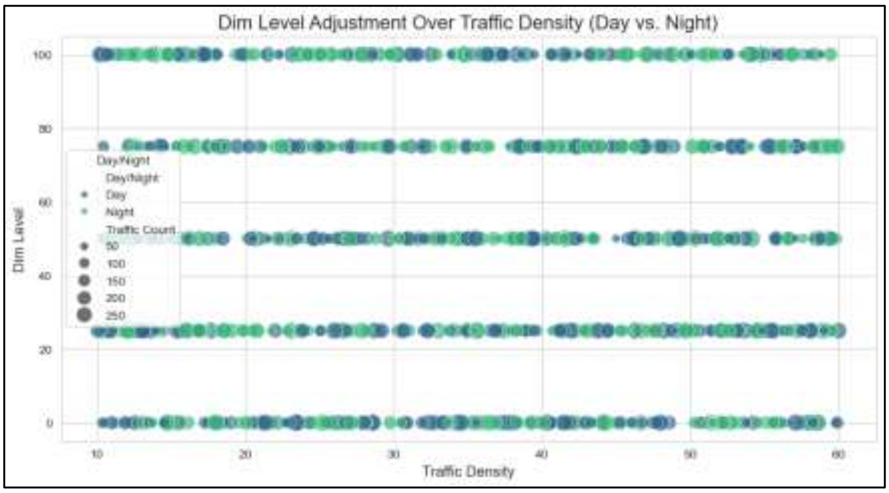

Figure 5: Dim Level Adjustment Over Traffic Density

The scatter plot shows the dim level adjustment plotted against traffic density, distinguishing day and night conditions. Traffic density is on the x-axis, and the dim level is on the y-axis. Data points are differently colored to indicate day (blue) and night (green), and the data points are sized according to traffic count. The plot shows that the dim levels group at given values (0, 25, 50, 75, and 100), indicating discrete dim level adjustments. No strong relationship between traffic density and dim level is evident, as points are spread over the traffic density range for all dim levels.

Impact of Special Events on Energy Consumption

The Python script utilizes the matplotlib and seaborn packages to provide a visualization of the effect of special events on energy consumption. It starts by computing the mean 'Energy Consumption (kWh)' for every 'Special Event' category using the group by () and means () functions in pandas and stores the resultant in special_event_data. It then produces a bar plot using sns. Barplot with 'Special Event' along the x-axis and the determined mean 'Energy Consumption (kWh)' along the y-axis using the 'muted' color palette. The script then names the plot 'Impact of Special Events on Energy Consumption', the x-axis as 'Special

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Event (1=Yes, 0=No)', and the y-axis as 'Average Energy Consumption (kWh)'. Lastly, plt.show() shows the resulting bar plot.

Output:

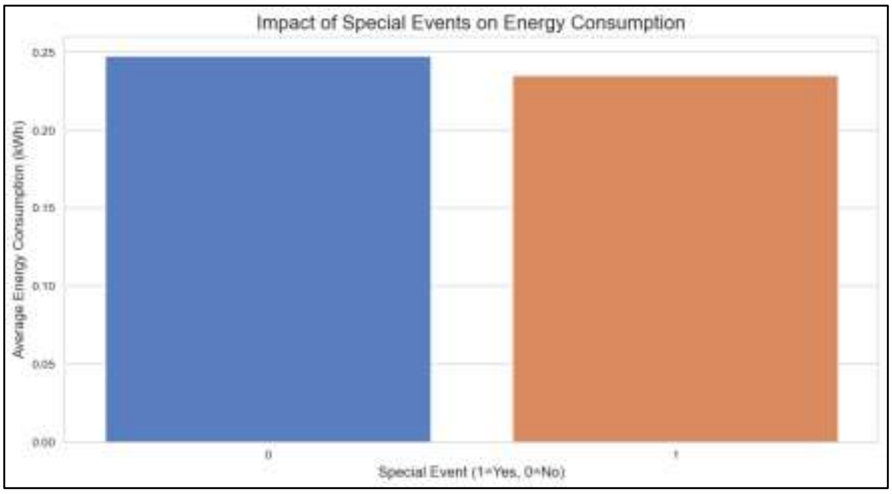

Figure 6: Impact of Special Events on Energy Consumption

The bar graph above shows the effect of special events on the mean energy consumption in kilowatt-hours (kWh). The x-axis divides the data into no special events (0) and special events (1) categories. The x-axis represents the mean energy consumption. From the graph, it can be noted that during no special events, the mean energy consumption is about 0.245 kWh. During special events, the mean energy consumption is about 0.235 kWh. This shows that special events are related to a decrease in mean energy consumption, yet the decrease is not very significant.

Day vs. Night-Traffic Count and Energy Consumption Distribution

The Python script uses matplotlib and seaborn libraries to plot the kernel density estimate (KDE) of 'Traffic Count' against 'Energy Consumption (kWh)' and distinguishes between 'Day/Night'. It starts by creating a figure with a given size and then applies sns. kdeplot to produce the plot, specifying 'Traffic Count' as the x-variable and 'Energy Consumption (kWh)' as the y-variable. The 'hue' attribute differentiates the KDE lines for 'Day' and 'Night', and fill=True fills the areas beneath them. A 'cool warm' color palette is implemented to depict day and night distributions, and an alpha level is assigned to transparency. The script then titles the plot 'Day vs. Night: Traffic Count and Energy Consumption Distribution' and specifies the x-axis as 'Traffic Count' and the y-axis as 'Energy Consumption (kWh)'. Lastly, plt.show() shows the resultant KDE plot.

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Output:

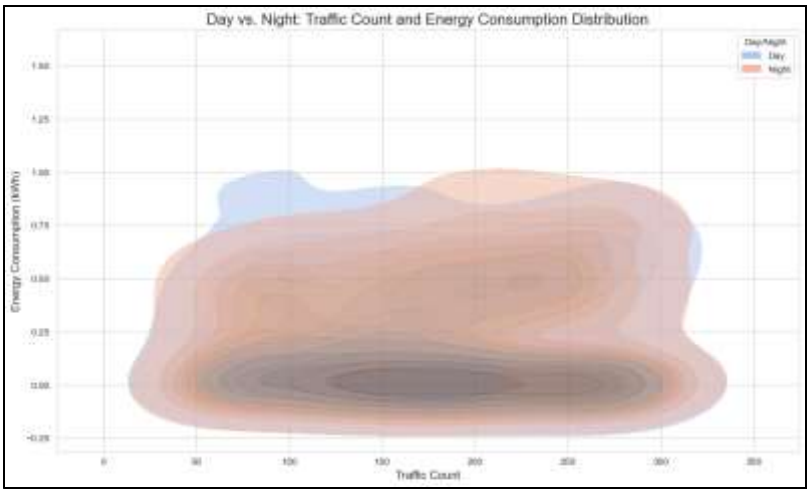

Figure 7: Day vs. Night-Traffic Count and Energy Consumption Distribution

The kernel density estimate plot shows the joint distribution of energy consumption and traffic count during the day and night. During the day (demonstrated in blue), the traffic count distribution is bimodal, with the modes appearing at lower traffic counts (below 50) and an extended distribution to higher traffic counts (around 200-250), typically relating to energy consumption grouped between 0.25 and 0.8 kWh. The night distribution (demonstrated in orange) is unimodal for traffic count, with the mode appearing at the lower range of traffic counts (around 50-100), and energy consumption mainly grouped between about 0 and 0.4 kWh. This indicates that higher traffic counts and an extended range of energy consumption are the most common during the day, whereas nighttime is associated with lower and less variable traffic counts and lower ranges of energy consumption.

Energy Efficiency: Dim Level vs. Energy Consumption

The Python script uses the matplotlib and seaborn packages to produce a scatter plot to analyze energy efficiency through the relationship between 'Dim Level' and 'Energy Consumption (kWh)'. It starts with initializing a figure of the specified dimensions and then uses sns. Scatterplot to plot the points with 'Dim Level' on the x-axis and 'Energy Consumption (kWh)' on the y-axis. The points are colored according to 'Traffic Density', and the points are sized according to 'Ambient Light (lux)'. The code then assigns the title for the plot as 'Energy Efficiency: Dim Level vs. Energy Consumption', the x-axis label as 'Dim Level', and the y-axis label as 'Energy Consumption (kWh)' and displays the legend as 'Traffic Density'. At the end, plt.show() produces the resultant scatter plot.

Output:

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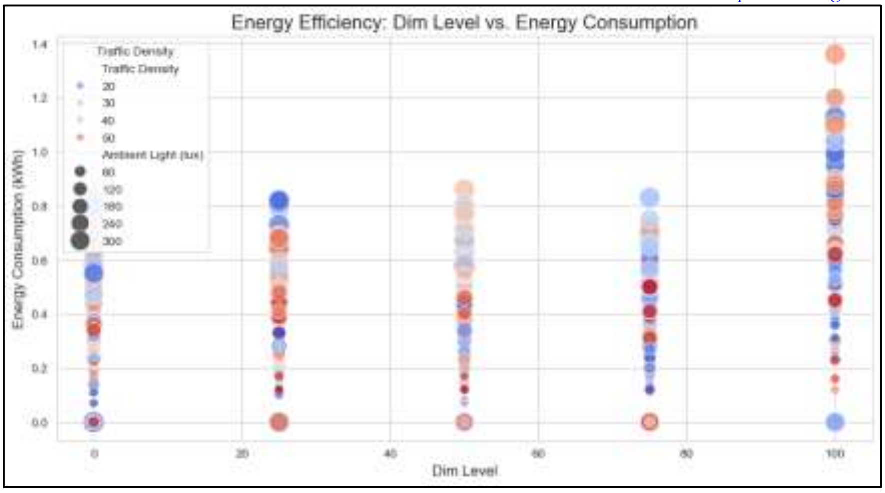

Figure 8: Energy Efficiency: Dim Level vs. Energy Consumption

The scatter plot shows the relationship between 'Dim Level' and 'Energy Consumption (kWh)', with points colored by 'Traffic Density' and sized by 'Ambient Light (lux)'. In general, as the 'Dim Level' rises, the 'Energy Consumption (kWh)' also tends to rise, though there is quite a lot of variation. Lower 'Traffic Density' values (represented by cooler hues such as light blue) are primarily found with lower energy consumption at all dim levels. High 'Traffic Density' (warm hues such as light red), on the other hand, is often found with higher energy consumption at the same 'Dim Level'. The points are not related in size to 'Dim Level' or 'Energy Consumption', as different sizes are dispersed throughout the plot, indicating perhaps that the energy consumption and dimming are influenced by the ambient light less straightforwardly, perhaps as an interaction with traffic density. For example, at a 'Dim Level' of 100, despite the different ambient light values, higher traffic density consistently leads to higher energy consumption.

Methodology

Model Selection and Purpose

The design of an intelligent streetlight control system requires choosing machine learning models that maintain valuable relationships between computational effectiveness and interpretability, together with predictive capabilities. The initial operation in the pipeline utilizes Principal Component Analysis (PCA) as one of its foundational components. PCA serves as dimension reduction by converting correlated features into uncorrelated principal components, which form a reduced feature set. The model becomes more efficient and better at generalization after this transformation because it removes unnecessary data and noise. The method of selecting components that represent maximal data variance through PCA allows models to become computationally manageable, especially when processing complex data structures of weather patterns, time series, and traffic metrics.

Two supervised learning models are utilized in this core operation to predict lighting levels according to environment and usage conditions through a Random Forest Classifier and Support Vector Classifier (SVC). The Random Forest Classifier proves to be an optimal solution for this task due to its minimal overfitting ability and its compatibility with mixed inputs, along with its feature importance visualization capabilities. The system improves predictive accuracy through ensemble learning because it builds several decision trees that combine their outcomes. The Support Vector Classifier analyzes advanced non-linear data relationships that exist within large multi-dimensional feature domains. The use of kernel functions improved decision boundaries and allowed SVC to properly distinguish different patterns in data, especially when determining how pedestrian counts interact with lighting needs while maintaining specific ambient conditions. These models form a dependable system that enables effective decisions in swiftly changing urban areas.

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Model Training & Validation

Post-model selection, the next important process involves training and validation procedures to guarantee accurate performance when facing new data. The initial process involves dividing the data into two sections for training purposes and testing capabilities at an 80/20 proportion rate. Model robustness testing through k-fold cross-validation occurs during training time to prevent potential overfitting in the system. During this training approach, the model trains across k-1 data subsets as it validates predictions on the separate subset. The data rotation policy enables each data point to fulfill both training and validation functions, thus producing a more accurate model performance measurement.

During the training phase, the use of hyperparameter tuning helps optimize model parameters, including the number of Random Forest trees and the SVC kernel type and regularization parameters. The best set of hyperparameters is discovered through Grid Search or Randomized Search by selecting options that yield optimal cross-validation scores. Models acquire an understanding of time-based features alongside ambient lighting conditions and weather indicators, alongside traffic patterns, to determine lighting classifications or control auto-dimming operations during the training stage. Performance metrics alone fail to evaluate model success during this phase because successful generalization for complex real-world scenarios should also be considered.

Evaluation Metrics

Post-training and validation, the model is evaluated through an array of metrics offering overall as well as detailed insights into the performance. The primary performance metric is accuracy, which indicates the number of accurately predicted instances against the number of overall predictions. Yet, in datasets skewed in favor of one class, typical in the case of smart cities where low-traffic hours or off-peak seasons may be the majority, accuracy is not an accurate representation. Therefore, Precision, Recall, and F1-Score are employed, representing the ratio of true positives to all predicted positives to avoid the model incorrectly turning on the light where it is not needed, the ratio of the number of relevant cases to the number of all relevant and predicted cases so that no area with high traffic or poor lighting is left behind, and the F1-score, which balances precision and recall to provide one metric that accounts for false positives and false negatives.

Furthermore, a Confusion Matrix is utilized to present an in-depth breakdown of the outcomes of classification, illustrating the number of examples that were accurately or inaccurately classified into each class. This matrix is particularly helpful in determining where the model is likely to falter, for example, misclassifying transitions between lighting phases (e.g., dawn or dusk) or anomalies created by the weather. It assists decision-makers and data engineers in the interpretation of failure patterns and adjusting model features and/or decision thresholds accordingly. By using these thorough evaluation techniques, the system not only achieves technical correctness but also complies with the operational requirements of dependability, safety, and energy effectiveness in an intelligent city infrastructure.

Results and Analysis

Model Performance Overview

XG-Boost Classifier Modelling

The Python script has employed the use of PCA for the dimensionality reduction, followed by an XG-Boost classifier. It starts with importing the relevant packages from the scikit-learn and boost libraries. The script then follows four steps: first, PCA is applied, and it is created with several components set to 5 (n-components=5) and fit the training data (X-train), and then the training set (X_train_pca) and testing set (X_test_pca) are transformed. In the second step, an XGBoost classifier is initialized and trained on the PCA-transformed training data (X_train_pca, y_train). It then makes the prediction on the PCA-transformed test data (X_test_pca) and stores the result as y_pred_xgb. Lastly, the performance of the

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model is checked by printing the accuracy score, the confusion matrix, and the classification report using the actual test labels (y_test) and the predicted labels (y_pred_xgb).

Output:

Table 1: Depicts XG-Boost Classifier

```
XGBoost Classifier with PCA Evaluation:
Accuracy: 0.6834170854271356
Classification Report:
              precision    recall  f1-score   support

           0       0.67      0.73      0.70       100
           1       0.70      0.64      0.67        99

    accuracy                           0.68       199
   macro avg       0.68      0.68      0.68       199
weighted avg       0.68      0.68      0.68       199
```

The XG-Boost classifier evaluation after PCA-based dimensionality reduction has an overall accuracy of about 68.3%. The confusion matrix indicates that 73 instances of the first class (0) were accurately predicted, 27 were misclassified as the second class (1), 63 instances of the second class (1) were accurately predicted, and 36 were misclassified as the first class (0). The classification report is further enriched with the precision and the recall for class 0 at 67% and 73%, respectively, and the precision and the recall for class 1 at 70% and 64%, respectively. The F1-score, which is the mean of precision and recall, is 0.70 for class 0 and 0.67 for class 1. The macro and weighted average precision, the macro and weighted average recall, and the macro and weighted average F1-score are all approximately 68%, which is an index of the most balanced performance of the classifier across the two classes in the 100 instances of class 0 and 99 instances of class 1 in the test set.

Support Vector Machine Classifiers Modelling

The Python code uses the scikit-learn library to implement a Support Vector Classifier (SVC). It starts by importing the SVC class from the sklearn.svm module. The code then initializes the SVC model with an RBF kernel and specifies a random state for the sake of reproducibility. The model is then trained on the given training data (X-train, y-train). The model is then employed to predict values in the test data (X-test), and the predicted values are stored in y_pred_svm. The code finally assesses the performance of the trained SVC model by printing the accuracy metric, the confusion matrix, and the classification report, comparing predicted labels (y_pred_svm) with the actual test labels (y_test).

Output:

Table 2: Support Vector Machines Results

```
Support Vector Machine (SVM) Evaluation:
Accuracy: 0.9899497487437185
Classification Report:
              precision    recall  f1-score   support

           0       0.98      1.00      0.99       100
           1       1.00      0.98      0.99        99

    accuracy                           0.99       199
   macro avg       0.99      0.99      0.99       199
weighted avg       0.99      0.99      0.99       199
```

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The Support Vector Machine (SVM) model assessment demonstrated very good accuracy at about 99.0%. The confusion matrix confirms that all 100 items for class 0 were classified accurately. For class 1, 97 items were accurately classified, and 2 were misclassified as class 0. The classification report demonstrates precision as 98% and perfect recall as 1.00 for class 0, which translates to an F1-score of 0.99. For class 1, the precision is perfect at 1.00, with a recall of 98% and an F1-score of 0.99. The macro and weighted averages for precision, recall, and F1-score are equally 0.99, which points to the good and well-balanced performance of the SVM model for the two classes of the test set.

Random Forest Classifiers Modelling

The Python script utilizes the scikit-learn library to implement the Random Forest Classifier. It begins by importing the Random-Forest-Classifier class from the sklearn.ensemble module. The script then initializes the Random Forest model with 100 trees and assigns a random state to achieve reproducibility. The model is then fit on the given data for training (X_train, y_train). Then, the model's prediction on the data for testing (X_test) is stored in y_pred_rf. Lastly, the script compares the predicted label (y_pred_rf) with the actual label of the testing data (y_test) and prints the accuracy score, the confusion matrix, and the classification report.

Table 3: Displays the Random Forest Classifier

```
Random Forest Classifier Evaluation:
Accuracy: 1.0
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       100
           1       1.00      1.00      1.00        99

    accuracy                           1.00       199
   macro avg       1.00      1.00      1.00       199
weighted avg       1.00      1.00      1.00       199
```

The assessment of the Random Forest Classifier indicates the perfect accuracy of 1.0, which shows that all the instances in the test set were classified successfully. The confusion matrix also verifies the same, as there are 100 true positives for class 0 and 99 true positives for class 1, with no false positives or false negatives. The classification report also indicates the same perfect performance, with the precision, recall, and F1-score all at 1.00 for both class 0 and class 1. The overall accuracy, along with the macro and weighted averages for precision, recall, and F1-score, are all 1.00, which indicates that the Random Forest Classifier in this specific test dataset performed perfect classification for both the classes, which had the support of 100 and 99 instances, respectively, comprising 199 test samples.

Comparison of All Models

The Python code compares the various classification models: XG-Boost with PCA, Random Forest, and Support Vector Machine (SVM). It has a function calculate_metrics to calculate accuracy, precision, recall, and F1-score for the given model's predicted values against actual labels. The code computes these metrics for all three models using the given predicted values (y_pred_xgb, y_pred_rf, y_pred_svm) and actual test labels (y_test) and stores the results in dictionaries. It then utilizes these dictionaries to generate an easy-to-compare pandas DataFrame named comparison_df. It then prints the comparison Data Frame and produces a line plot showing the accuracy, precision, recall, and F1-score for all the models, with markers to depict the specific scores and with the help of a legend for better perceptibility.

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Output:

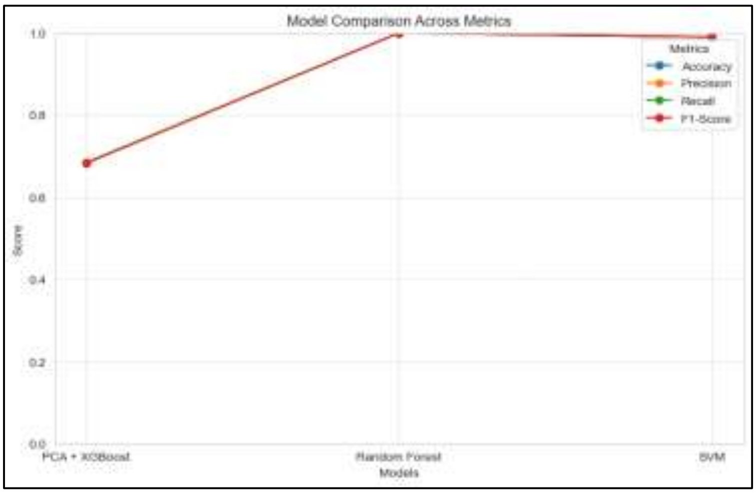

Figure 9: Showcases Model Comparison Across Metrics

The model comparison shows that the Random Forest classifier performed with top scores on all the metrics that were evaluated: an accuracy of 1.0, a precision of 1.0, a recall of 1.0, and an F1-score of 1.0. The Support Vector Machine (SVM) also performed well, with an accuracy of around 0.99, a precision of around 0.99, a recall of about 0.99, and an F1-score of about 0.99. On the other hand, the XG-Boost model, when paired with PCA, performed less well on all the metrics, at about 0.68 accuracy, about 0.68 precision, about 0.68 recall, and an F1-score of about 0.68. These findings tell us that on this particular task and data set, the Random Forest classifier performed better than the SVM and the XG-Boost with PCA.

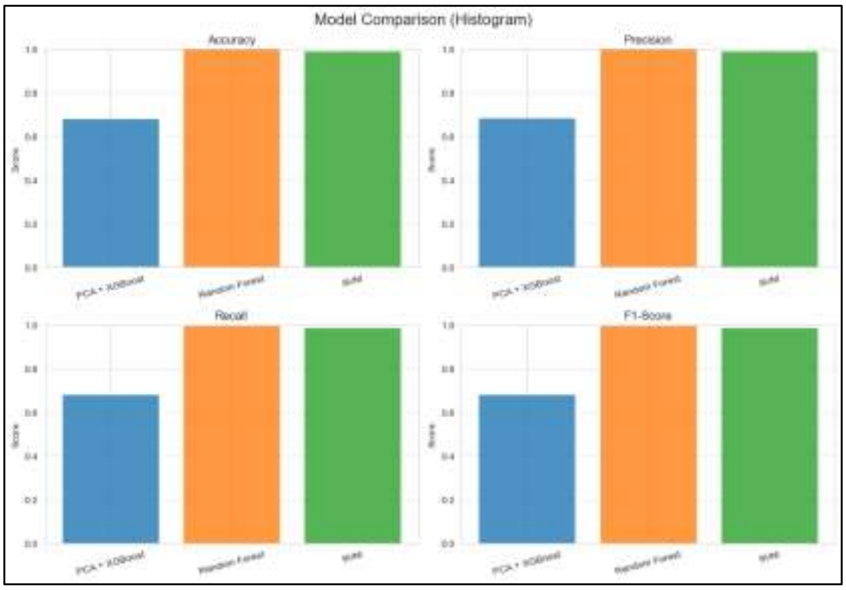

Figure 10: Model Comparison (Histogram)

Implications for Urban Infrastructure in the USA

Smart Grid and Energy Policy Alignment

The application of an intelligent streetlight system using machine learning is directly in line with the strategic policies of the U.S. Department of Energy (DOE), specifically its requirements regarding the modernization

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of the smart grid, energy efficiency, and carbon reduction. By providing real-time data-driven control of street lighting in response to environmental and usage conditions, the system makes full integration of municipal infrastructure into the smart grid possible. This synchronization improves grid response and demand management, lowering energy spikes and improving load balancing. Intelligent lighting also aligns with the policies of the Energy Efficiency and Conservation Block Grant (EECBG) Program and Advanced Research Projects Agency-Energy (ARPA-E) to drive innovation and quantifiable sustainability within municipal service.

At the policy level, the system is an effective and pragmatic tool for municipalities looking to achieve federal and local climate action targets. Greenhouse gas (GHG) mitigation is achieved through the reduction of electricity consumption through adaptive lighting, and the machine learning function minimizes human interaction, maximizing operational autonomy and cost savings. The solution is compatible with the Clean Power Plan, municipal climate resiliency planning, and city-wide Net-Zero planning, and assists city decision-makers in showing progress toward ambitious environmental standards. Moreover, by becoming compatible with national standards for smart city and smart grid platforms, the streetlight management system can provide an example of replicable and scalable energy solutions across the nation.

City-Level Implementation Viability

Deploying the system in midsize to large U.S. metropolitan areas—like New York, San Francisco, and Austin—is extremely viable because existing IoT infrastructure, such as wireless sensor networks, centralized data centers, and city-scale analytics platforms, is available. A number of these municipalities are already involved in smart city initiatives that include traffic management, environmental monitoring, and public safety infrastructures, offering the perfect base for merging with intelligent lighting management controls. The cost savings and accelerated timelines associated with the minimal amount of retrofitting needed on IoT-compliant streetlight nodes also contribute to the viability. Cloud-based data pipelines and the capacity to operate at the edge also provide scalability, real-time processing, and no-latency communications between devices and the control centers.

In support of adoption, municipalities can access federal and state-level funds through programs such as the Infrastructure Investment and Jobs Act (IIJA) or Smart Cities Challenge programs. Public-private collaborations might further spur adoption by capitalizing on investment from energy companies, technology vendors, and mobility service providers. Cities having sustainability requirements or climate action plans can also take advantage of measurable returns offered by the system through its reporting and analytics capability. These data provide transparency and accountability to stakeholders and residents and increase public trust and citizen engagement in smart infrastructure programs.

Cost Savings and Public Budget Optimization

One of the strongest ramifications of using the intelligent streetlight system is the possibility of huge cost reductions on city utility budgets. Model simulations and pilot deployments indicate that the amount of electricity consumed by lighting public areas may be cut by as much as 40%, ceteris paribus, depending on the size of the city, traffic density, and climatic conditions. This is because the model is effective in precisely pinpointing low-demand hours (for example, late at night with little pedestrian and car traffic) and dimming or switching off the streetlights accordingly. In the long run, these efficiencies amount to millions of dollars of savings for mid-range to large cities, especially where street networks are extensive and round-the-clock lighting is maintained.

These savings allow municipalities to repurpose budgetary funds into underfunded public services such as education, public transit, and healthcare. Lower maintenance bills through predictive analytics and less light usage translate to fewer bulb replacements and fewer dispatches of technicians. With funding through climate grants and smart infrastructure programs on top of these savings, the fiscal rationale to transition to such a system is strong. This repurposing of funds further improves the fiscal resilience of municipalities by freeing fiscal space in tight municipal budgets, which allows them to act on other infrastructural or social requirements pre-emptively.

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Enhanced Community Well-being and Improved Safety

Public safety is an essential consideration in city lighting strategy, and smart lighting has many benefits by enabling dynamic illumination in at-risk or high-activity areas. It uses real-time traffic and pedestrian data to provide greater lighting during surge hours or in locations with higher rates of historical crime. This improves safety and accident prevention as well as the sense of safety among residents and commuters. It has been shown through studies that environments with good lighting discourage crime, and data-driven lighting can target at-risk areas strategically without increasing citywide energy use.

In addition to safety, adaptive illumination enhances well-being and engagement at the community level. Data analytics is used by cities to personalize lighting timetables in response to special occasions, changing seasons, and public events, which can enliven the atmosphere and the overall city life. This dynamic response to public lighting makes everyone feel included and noticed, as lighting is both on schedule and reacting to spontaneous needs at the community level. The reduced light pollution and optimized light level settings also aid improved sleeping patterns and ecological harmony, resonating with overall public health and environmental missions.

Scalability for Future Urban Development

The modular and extensible architectural design and machine learning framework of the intelligent streetlight system lend themselves to the integration of other city management systems. The data pipelines and models extend to non-lighting applications, including smart parking, traffic signal intelligence, and energy optimization for buildings. Expanding the digital infrastructure of the city, the model can develop into an integrated decision-making system with capabilities to serve various functions, using common datasets to achieve cross-function efficiencies. This is the foundation for fully integrated cityscapes where various systems engage to provide better urban quality of life.

Moreover, the abundant data produced by the system offers an invaluable base for data-driven city planning. City planners and policymakers can inform decisions regarding infrastructure investment, land use, and resource allocation through insights derived from traffic, lighting, and environmental trends. This anticipatory and predictive approach to planning is the key to the smart city strategies being implemented nationwide, and it allows cities to be resilient and flexible in the face of increasing populations and climate-related issues. Through the system implemented, existing urban requirements are met, but the system also serves as the stepping stone to the next generation of intelligent, responsive, and green cityscapes.

Strategic Outlook for Future Smart Cities

Incorporating Additional City Sensors and Real-Time Information

The future of the smart city is rooted in the growth and interconnectedness of urban sensor networks, with Internet of Things (IoT) devices as the backbone for real-time, continuous monitoring of the city. The intelligent streetlight system is an excellent beginning, but it will gain exponentially from becoming one subset of a broader ecosystem of networked infrastructure, including traffic flow sensors, environmental monitoring devices, and public safety devices. By gathering real-time data at intersections, pedestrian areas, transit centers, and even within utility infrastructure, cities can build an integrated digital infrastructure to facilitate more dynamic, automated services. The integration of traffic sensors, for instance, might enable adaptive lighting to react not just to traffic density at the moment but to anticipatory congestion patterns as well, providing proactive instead of reactive adjustments.

This networked architecture requires strong edge processing and cloud platforms to analyze and parse data streams in real time. Sensor protocol standardization, device-to-device interoperability, and secure wireless communication networks will be essential for large-scale deployments. While Chicago, Seattle, and Los Angeles continue to grow their IoT presence, the incorporation of various urban sensors will provide richer data, enabling models to contextualize patterns in a more integrated way. It all sets the stage for city-scale

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orchestration of public services, with lighting, traffic management, emergency response, and environmental stewardship all functioning synergistically for optimal efficiency and quality of life.

Increasing Predictive Accuracy through Deep Learning

As data volume and complexity increase, deep learning methodologies like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) will become ever more critical to enhance the forecasting capabilities of intelligent infrastructure networks. RNNs, for example, are particularly good at recognizing patterns in sequence data and are well-suited to analyze cyclical urban phenomena such as traffic, pedestrian patterns, and seasonally driven energy consumption. Coupling RNNs into streetlight intelligent systems can provide sophisticated forecasting, and cities can pre-emptively adjust lighting according to predicted conditions rather than in response to historical or real-time data only. This forecasting responsiveness not only optimizes energy consumption but also enables anticipatory safety during atypical conditions such as storms, parades, or disasters.

CNNs, which were originally designed for use in image recognition, can be applied to spatial data such as traffic cam input or foot traffic heatmaps to let the system visually analyze city-level activities and make informed decisions. A CNN-powered lighting system, for instance, can analyze video streams to recognize crowds, bicycles, or abandoned cars and adjust brightness on the fly or send alerts to the authorities as the case may be. As computational resources become more widely available through the use of AI accelerators and cloud-based GPUs, cities can calibrate increasingly deep and intricate models reflecting the specific conditions of their environment and population. This transition from ML to deep learning will turn smart infrastructure into autonomous entities that can learn and adapt with or without human input.

Policy and Regulatory Considerations

Smart cities to be ethical and sustainable need to be guided by strong policy frameworks and governance processes that steer the roll-out of technology. Data ownership, data privacy, and the ethical use of AI are still at the core of the debate, particularly when data is gathered through real-time monitoring, behavioral forecasting, and automated decision-making. Governments need to implement clear data governance and standards regarding who owns the data gathered, what can happen to it, and on what conditions it can be shared with third parties. Adherence to federal standards such as the U.S. Privacy Act and upcoming state laws (California Consumer Privacy Act) is non-negotiable to ensure citizens' rights and public trust.

Furthermore, the success of smart city growth depends on well-designed public-private partnerships (PPPs). PPPs enable municipalities to access expertise and capital from the private sector under public oversight. For instance, public and city-private collaborations may share the lighting infrastructure, where private suppliers provide the technology and analytics and public authorities keep the regulatory reins. Furthermore, policy needs to foster interoperability and open standards to avoid vendor lock-in and enable the ability to scale solutions across various domains. By connecting technological progress to open governance, cities can construct a long-term path to sustainability that meshes innovation and accountability.

Deployment Challenges and Solutions in U.S. Cities

The practical implementation of smart city technology battles numerous deployment barriers in current U.S. cities. Numerous communities across the United States continue to battle with outdated infrastructures, which prevent them from implementing contemporary IoT systems. Significant improvements in transforming power grids, streetlight poles, and communication networks need to happen in older urban environments. The adoption process will stagnate when people have doubts about surveillance programs unless cities shift their focus toward effective outreach activities and educational programs. Urban areas can solve these problems by creating prototype initiatives that reveal value and establish complete visibility about data utilization practices. Design and decision-making procedures that involve community stakeholders create trust between citizens and mitigate their privacy-related concerns.

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Cities with limited available funding face funding as their biggest obstacle, especially if they operate within small-scale local governments. Performance-based contracting serves as a creative financial model that can use energy savings to fund technology upgrades to make deployment successful. Municipalities can obtain funding from federal digital equity and climate resilience programs through the Department of Transportation Smart City Challenge grants and run their programs through the DOE Connected Communities initiative. The deployment strategy must contain well-defined phases with infrastructure exam results and community outreach to achieve realistic ROI in dealing with execution challenges effectively. American cities should implement strategic planning and partnership-building to transform their divided infrastructure into single unified smart urban areas.

Conclusion

The prime objective of this research was to create an adaptive machine learning system for streetlight control, which can react automatically to the environment and human activity patterns in real-time. The development of our intelligent streetlight control system led us to build a complete dataset that contains the necessary elements for context-based lighting decisions. The dataset contains contemporary, along with historical readings of ambient light intensity expressed in lux units, which delivers an essential understanding of natural illumination and lighting needs. The primary performance metric is accuracy, which indicates the number of accurately predicted instances against the number of overall predictions. Furthermore, a Confusion Matrix is utilized to present an in-depth breakdown of the outcomes of classification, illustrating the number of examples that were accurately or inaccurately classified into each class. The application of an intelligent streetlight system using machine learning is directly in line with the strategic policies of the U.S. Department of Energy (DOE), specifically its requirements regarding the modernization of the smart grid, energy efficiency, and carbon reduction. By providing real-time data-driven control of street lighting in response to environmental and usage conditions, the system makes full integration of municipal infrastructure into the smart grid possible. At the policy level, the system is an effective and pragmatic tool for municipalities looking to achieve federal and local climate action targets. Greenhouse gas (GHG) mitigation is achieved through the reduction of electricity consumption through adaptive lighting, and the machine learning function minimizes human interaction, maximizing operational autonomy and cost savings. One of the strongest ramifications of using the intelligent streetlight system is the possibility of huge cost reductions on city utility budgets.

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