FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 8 No. 2, April, 2024, pp 390 - 398
DOI: https://doi.org/10.33003/fjs-2024-0802-2320

INTELLIGENT LIGHTING CONTROL SYSTEMS FOR ENERGY SAVINGS IN HOSPITAL BUILDINGS USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Lighting control systems are essential in modern building automation and smart homes, efficiently managing illumination to enhance energy conservation and user comfort. This project tackles energy consumption challenges in hospital buildings by introducing Intelligent Lighting Control Systems (ILCS) that take natural light and occupancy into account, driven by Artificial Neural Networks (ANN) and machine learning algorithm. In this study, data was collected from the light and motion sensor readings, processed, and designed a lighting control system employing a feedforward neural network and machine learning algorithm. This research found that a linear regression algorithm surpassed the ANN-based system in this context. Implementation of a prototype was carried out, tested on a hardware, and obtained the expected results. This research marks progress towards optimizing energy use in hospital buildings and contributing to sustainability endeavors. By combining ILCS and machine learning, it offers a promising approach for more efficient and eco-friendly lighting systems.

Keywords: ANN, Arduino, Energy savings, Lighting control systems, Microcontroller

INTRODUCTION

The traditional lighting control system has been unable to meet people's diverse lighting requirement, but also cannot achieve the purpose of energy saving and consumption reduction (Wang *et al*., 2021). It is fundamental to find innovative solutions that are sustainable from the perspective of energy generation, management and environmental protection (Isiyaku *et al*., 2023). These solutions will provide a promising future in terms of energy sources meeting energy demand, together with maintaining the environment (Mahlia, and Rizwanul, 2021) and the use of artificial intelligence (AI) in building automation systems has revolutionized the way we design and manage building environments. Intelligent lighting control systems using artificial neural networks (ANNs) is a prime example of this innovation, which offers significant energy savings and improved occupant comfort in buildings. Lighting control systems have traditionally relied on simple sensors and timers to turn lights on and off. However, these systems do not consider factors such as occupancy, natural light levels, and individual preferences. As a result, energy waste and occupant discomfort can occur, leading to negative impacts on the environment and building performance (Khairul and Mohd, 2018). Intelligent lighting control systems using ANNs offer a more sophisticated approach to building lighting management. ANNs are capable of learning patterns in data related to lighting usage, occupancy levels, and natural light levels. This allows for the development of a customized lighting schedule that is optimized for each individual space within the building.

Related Works

Ding and Yu (2023) worked on the development of a convolutional neural network (CNN) in an embedded building lighting control system to improve image recognition accuracy and reduce energy consumption. Currently, lighting control systems rely on sensors to detect people's presence or absence, but the accuracy of image detection is limited. Results showed that the image recognition accuracy of the CNN-based embedded control system was very high, with a difference between actual and positioning position ranging from 0.01 to 0.20 m. Moreover, comparing the luminous flux of the designed system with natural light and the system without intelligent control, the energy savings was about 40%.

Alim *et al*., (2022) developed a cost-effective, remote-access indoor lighting control system using sensors like ultra-wide band and lux sensors to collect location and brightness data. Machine learning algorithms predict suitable lighting conditions, maintaining a brightness range of 200-400 Lux for various settings. It's ideal for homes, offices, schools, and apartments, composed of low-cost, easily replaceable components, offering cost and power savings. Power consumption prediction wasn't included as initially intended.

In the work by Wang and Lv (2022), increasing energy consumption in underground parking garages was addressed. They proposed an IoT-based lighting control system using the ESP32 chip and sensors to detect movement and light intensity. The system controls lamp brightness and switches based on this data, saving energy by turning lights on when cars arrive and off when they leave. They also explored Wi-Fi protocols, wireless mesh networking, and IoT cloud platforms. However, security risks and implementation costs should be considered.

Lee *et al*., (2018) developed a dimming lighting control system using general illumination and location-awareness technology to address indoor illuminance imbalances. They tested three cases: (1) dimming control, (2) dimming control with location-awareness, and (3) dimming control with both technologies. Case 3 reduced lighting energy by 47.9-64.2% compared to Case 1 and improved indoor lighting uniformity by 17.8-49% compared to Case 2. These findings demonstrate the effectiveness of Case 3 in enhancing energy efficiency and indoor lighting comfort. However, the study's evaluation was performed in an artificial environment, which may not fully reflect real-world conditions.

Okomba *et al*., (2017) presents an intelligent energy-saving streetlight system that is designed to minimize energy consumption by up to 30% by activating the streetlights only during specific periods. It incorporates random logic and light-dependent resistors (LDR) as input sensors strategically placed for maximum efficiency. In busy areas, such as roads, the system detects vehicle headlights consistently hitting the LDR for 90 seconds, triggering the streetlight to dim. It remains in this dim state until the LDR stops receiving light for 60 seconds, at which point it returns to full brightness. The system's operation is controlled by one-shot pulse generators and utilizes electromagnetic relays for switching. Evaluation using car headlights demonstrated that the system effectively reduces energy consumption for street lighting.

Burmaka *et al*., (2020) assessed the cost and energy savings of using artificial lighting control systems in residential stairwells. Results showed that combining astronomical relays and motion sensors significantly reduced electricity consumption, with savings ranging from 43.31% to 97.73%, depending on the light source. The study also provided data on residents' movement patterns and confirmed the economic and energy benefits of these lighting systems.

Pompei *et al*., (2020) focused on reducing CO_2 emissions in the building sector, with a specific emphasis on building lighting, responsible for 20% of construction industry electricity usage. Using the UNI EN 15193-1:2007 standard and the LENICALC software by ENEA, the authors assessed the energy consumption of artificial lighting, employing different LENI calculation methods. They analyzed an educational building to evaluate the impact of daylight and occupancy lighting controls and their combination on energy consumption.

Simulations using LENICALC revealed that combining these control systems resulted in significantly higher energy savings compared to using each control system separately.

Choi *et al*., (2022) aimed to address fatigue in individuals by developing personalized smart lighting solutions for their homes. Real-time analysis of occupant activity data through a mobile app was used to assess fatigue levels based on Metabolic Equivalent Tasks (METs). Multiple regression analysis was employed to validate the accuracy of this quantification method. The research proposed luminous environment solutions, including illuminance and Correlated Color Temperature (CCT), tailored to different activity and fatigue levels. These solutions were tested in three mock-up spaces. The study supports the development of human-centric building technologies by offering customized indoor lighting environments.

Seyedolhosseini *et al*., (2021) designed a smart indoor lighting system for multiple zones to enhance user comfort and reduce energy consumption. They developed an efficient control mechanism using optimization and clustering algorithms to minimize photodetectors. A neural network-controlled luminaire dimming, and auxiliary photodetectors analyzed daylight variations. Results showed that up to 82% of photodetectors could be removed with no loss in accuracy. The Mean Absolute Error for achieving desired illuminance was below 23.6lx, making this approach effective for smart indoor lighting in different environments.

Odiyur *et al*., (2021) explores daylight harvesting for energy efficiency. They used ECO TECH software to simulate daylight contribution in an office building in Chennai, India, considering factors like building orientation and reflectance values. The study aims to promote research in this field of energy-efficient lighting strategies.

MATERIALS AND METHODS

This section outlines the methodology employed in the development and evaluation of the lighting control system utilizing feed forward neural networks as a fundamental component while exploring other machine learning algorithms which is the software implementation aspect of this project. The hardware implementation features the design and implementation of a hardware prototype that includes, a microcontroller, sensors, and LEDs to depict the operation of the entire system. The system block diagram is shown in Figure 1 and has two main component which is the hardware and the software component.

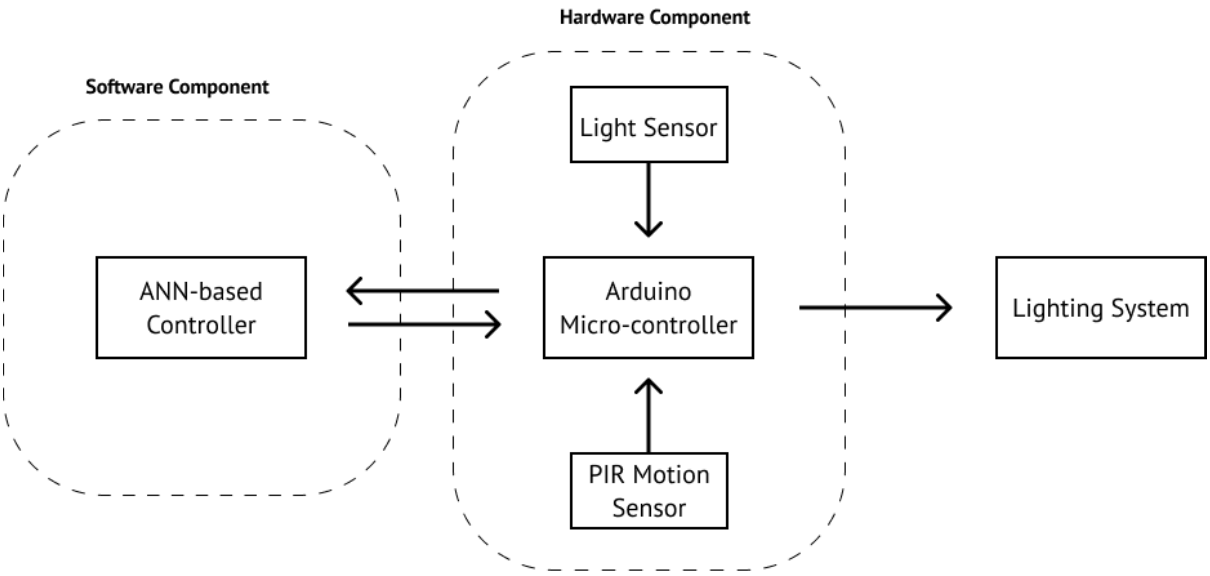


Figure 1: Block diagram of the system

Hardware Component

The hardware component consists of the microcontroller unit and the sensing unit. Using these 2 units, the hardware component acts as a middleman between the software components and the lighting system, using sensors to collect data that is fed into the software component to make decisions and then actuates the decision on the lighting system.

Arduino Microcontroller Unit: The Arduino microcontroller is a microprocessor embedded circuit board with open-source software development environment that allows easy development of microcontroller-based devices. It allows for the development of micro-controlled systems that can be adapted to needs (Okomba *et al*., 2015). The Arduino nano board serves as the primary controller for the system, responsible for collecting data from the sensors, processing the data, and sending commands to adjust the lighting levels of the LED.

Sensing Unit: To sense the occupancy and ambient lighting conditions of the hospital rooms, a combination of passive infrared (PIR) sensor and an LDR sensor was used. The PIR sensor detects human presence and movement, while the light sensor measures the ambient lighting levels in the room. Light-dependent resistors, also known as LDRs or photoresistors, are electronic components commonly used to detect light presence and intensity. They work based on the principle of photoconductivity, with their resistance changing in response to detected light (Yantidewi *et al*., 2022). These sensors were connected to the Arduino nano board via digital and analog input pins, respectively.

The microcontroller employs pulse width modulation (PWM) to regulate luminance levels by adjusting the mean electrical power to the LED based on instructions from the intelligent lighting controller. These instructions rely on occupancy patterns and ambient light data collected by sensors. To facilitate robust communication between hardware and software, a wired USB protocol connects the Arduino nano board, which transmits data to a separate computer for processing and lighting control decisions.

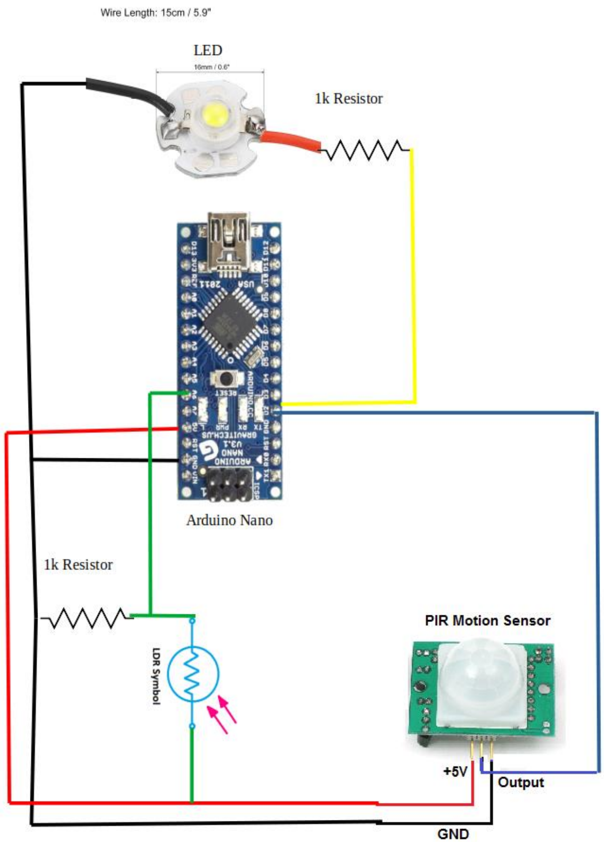


Figure 2: Circuit Diagram of the System

Software Implementation

The software implementation process comprised several sequential phases. Initially, we conducted data acquisition and preprocessing using a dataset containing approximately 56,000 rows with essential columns, including occupancy detection (0 for no occupancy, 1 for occupancy based on PIR motion sensor readings), light intensity (ranging from 0 to 1, derived from LDR sensor data representing ambient light levels), and an output column (also ranging from 0 to 1) representing the desired lighting level.

A feed forward neural network whose architecture has 2 input features, 2 hidden layers with 64 and 32 units, and an output layer with a linear activation function was used as a model in the design of the lighting control system. The model was compiled with the Adam optimizer, binary cross-entropy loss function, and accuracy metric. The model was trained for 100 epochs using a batch size of 32. Machine learning algorithms such as Support Vector Machines (SVM), Decision Tree Regressor (DTR) and Linear Regression were also used in the design of the lighting control system.

The machine learning and neural network program code was written on visual studio code with python. The microcontroller program code was written on Arduino IDE environment with Arduino C# programming language. Also, it was compiled on the Arduino IDE with the inbuilt compiler. It is important to note that all software operations were conducted on a laptop computer equipped with a 1GHz Intel Core i5 10th gen processor, 16GB RAM, and 512GB ROM storage, providing the necessary computational resources for the implementation.

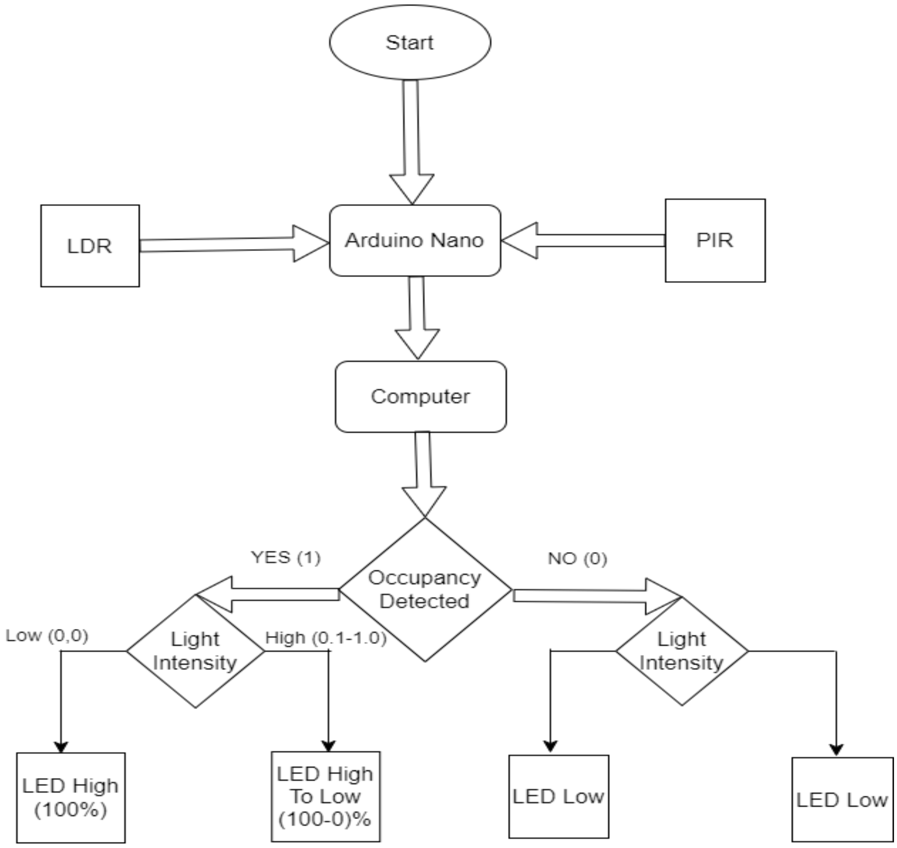
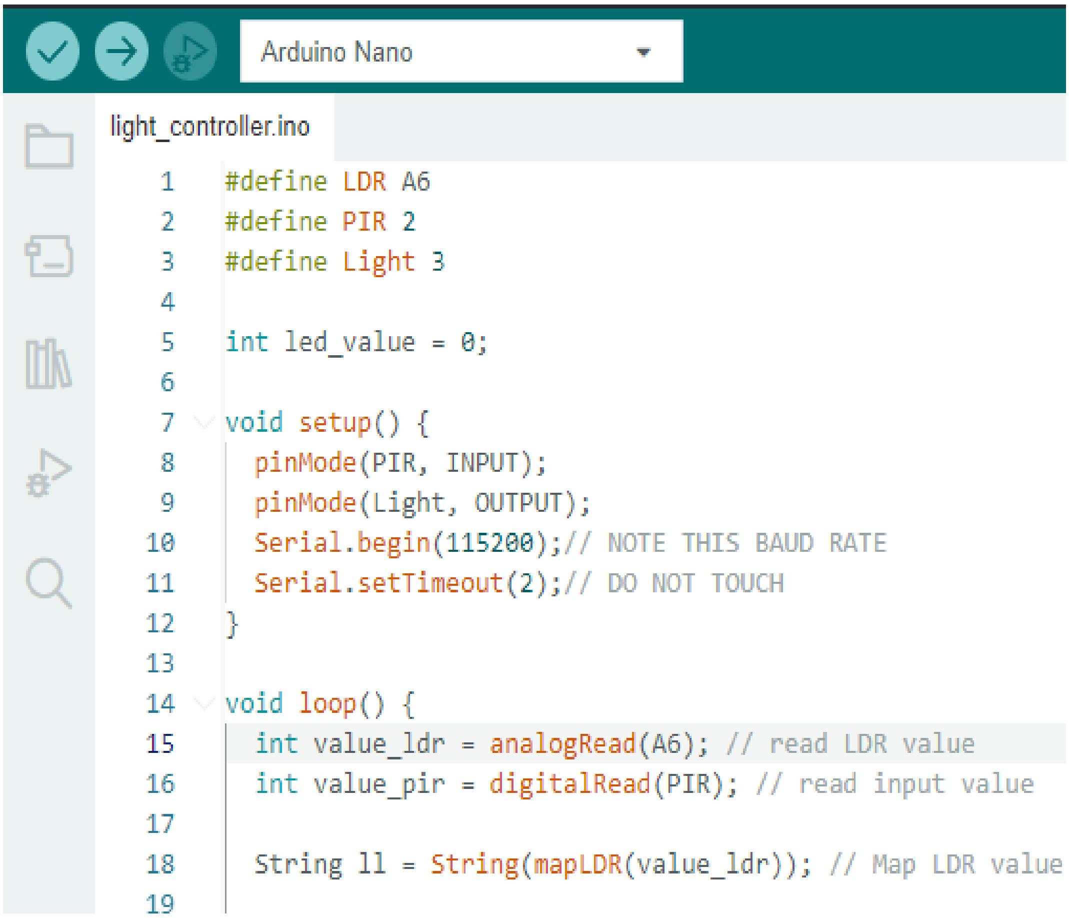


Figure 3: Flow Chart of the System




```
#define LDR A6
#define PIR 2
#define Light 3

int led_value = 0;

void setup() {
  pinMode(PIR, INPUT);
  pinMode(Light, OUTPUT);
  Serial.begin(115200);// NOTE THIS BAUD RATE
  Serial.setTimeout(2);// DO NOT TOUCH
}

void loop() {
  int value_ldr = analogRead(A6); // read LDR value
  int value_pir = digitalRead(PIR); // read input value

  String ll = String(mapLDR(value_ldr)); // Map LDR value

```

Figure 4: Code snippet showing microcontroller control logic.

RESULTS AND DISCUSSION

The performance of each trained model was evaluated using the Mean squared error and the R2 score. The result is presented in the table below.

Table 1: Performance Results for Different Trained Models

MODEL	MEAN SQUARED ERROR	R2 SCORE
Decision Tree Regression (DTR)	0.103491	-1966.700
Support Vector Machine (SVM)	0.106923	-1140846.193
Feed-Forward Neural Network (FFNN)	0.105697	-0.002
Linear Regression (LR)	0.103473	-15365.474

Table 1 shows the result of training four different machine learning models for the intelligent lighting control systems. The mean squared error (MSE) and R2 score are shown for each model. The MSE is a measure of the error between the predicted and actual values, while the R2 score is a measure of the goodness of fit of the model. The Linear Regression model has the lowest MSE, indicating that it is the best performing model with limited error but it has wide negative values of R2. Wide negative value of R2 indicates that the chosen model does not follow the trend of the data and is not appropriate for the data. This suggest that the FFNN will on the average perform well in predicting the lighting levels of the intelligent lighting control system than the rest algorithms since it has very low negative R2 value and considerable MSE value compared to the rest.

Results showing sensor readings and lighting control system predictions for each trained model

A comprehensive overview of the system's sensor readings and output light intensity for each model created for the lighting control systems (which in turn controls the LED brightness). These conclusions are drawn from a well-managed record that the system keeps while it is in operation. Tables and charts are utilized to display the findings and illustrate how each model performed and how much energy was saved. In a bid to compare and determine how much energy was saved, the brightness of the LED connected to the controller was compared to that of another LED which was not.

i. Decision Tree Regression (DTR)-based Lighting control system

The decision regression model stood out with a Mean Squared Error (MSE) of 0.103491. It performed admirably, although it showed slightly lower performance compared to the linear regression model. Looking at the data gathered from its log, the system managed to be around 49% more energy-efficient throughout a typical day of operation.

Table 2: Sensor readings and predictions for DTR-based lighting control system

Motion sensor readings	Light sensor readings	Predicted light intensity	Time of day
0	0.4	0.4	Morning
1	0.6	0.6	
0	0.8	0.4	Afternoon
1	0.8	0.4	
0	0	0	Night
1	0	0.8	

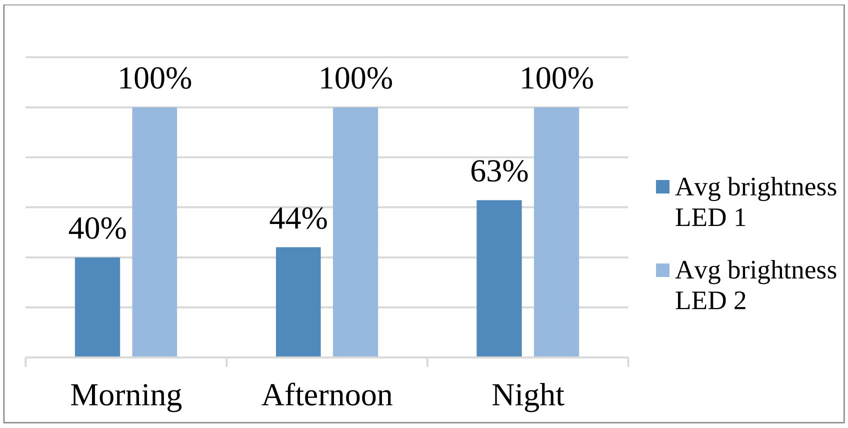


Figure 5: Average LED brightness of DTR-based lighting control system at different times of the day

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ii. Feed Forward Neural Network (FFNN)-based Lighting control system

The Feedforward neural network model didn't perform well in the lighting control systems. According to the system log, there was no energy saved during a day of use.

Table 3: Sensor readings and predictions for FFNN-based lighting control system

Motion sensor readings	Light sensor readings	Predicted light intensity	Time of day
0	0.2	1	Morning
1	0.7	1	
0	0.3	1	Afternoon
1	0.5	1	
0	0.2	1	Night
1	0	1	

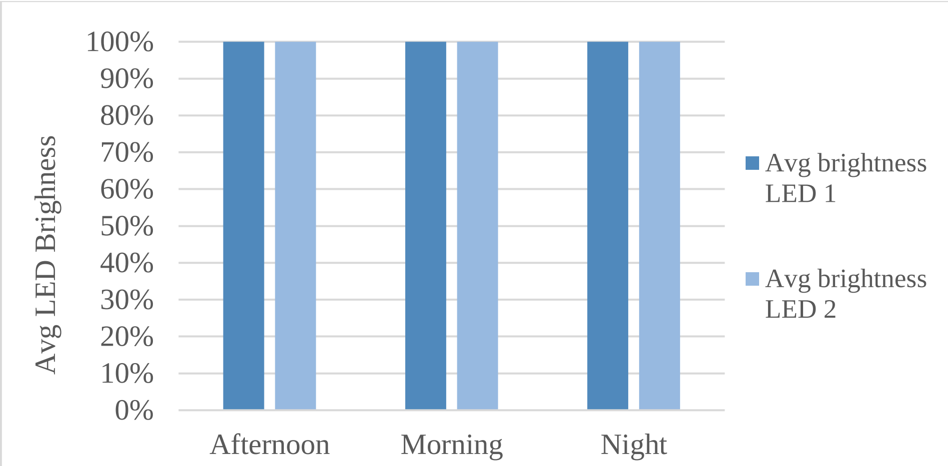

Figure 6: Average LED brightness of FFNN-based lighting control system at different times

iii. Support Vector Machines (SVM)-based Lighting control system

Table 4: Sensor readings and predictions for SVM-based lighting control system

Motion sensor readings	Light sensor readings	Predicted light intensity	Time of day
0	0.7	1	Morning
1	0	1	
0	0.8	1	Afternoon
1	0.2	1	
0	0	1	Night
1	0.1	1	

The SVM model didn't perform well in the lighting control systems. According to the system log, there was no energy saved during a day of use.

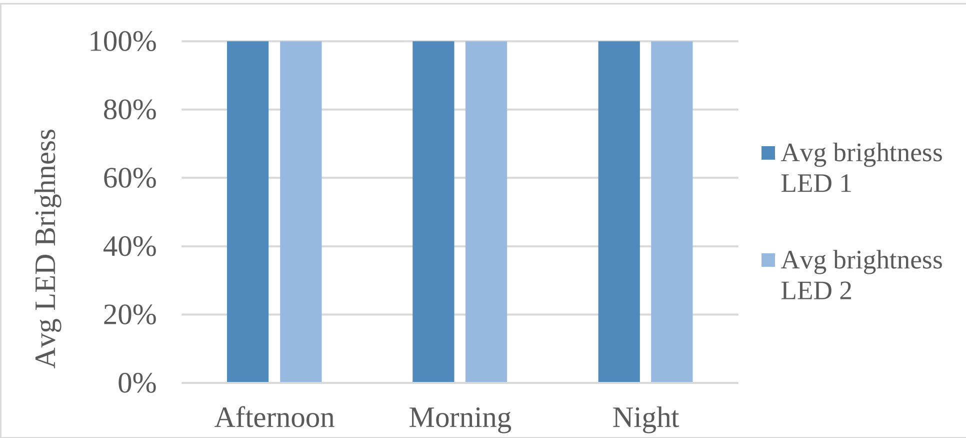

Figure 7: Average LED brightness of SVM-based lighting control system at different times

iv. Linear Regression-based Lighting control system

The Linear regression-based model stood out with the best performance when used in the lighting control system. Analyzing at the data kept in the system's log for a day shows an average of 54% emerging savings which outperforms any other models used in this project.

Table 5: Sensor readings and predictions for Linear Regression-based lighting control system

Motion sensor readings	Light sensor readings	Predicted light intensity	Time of day
0	0.2	0.2	Morning
1	0.7	0.5	
0	0.9	0	Afternoon
1	0.6	0.8	
0	0	0.2	Night
1	0	1	

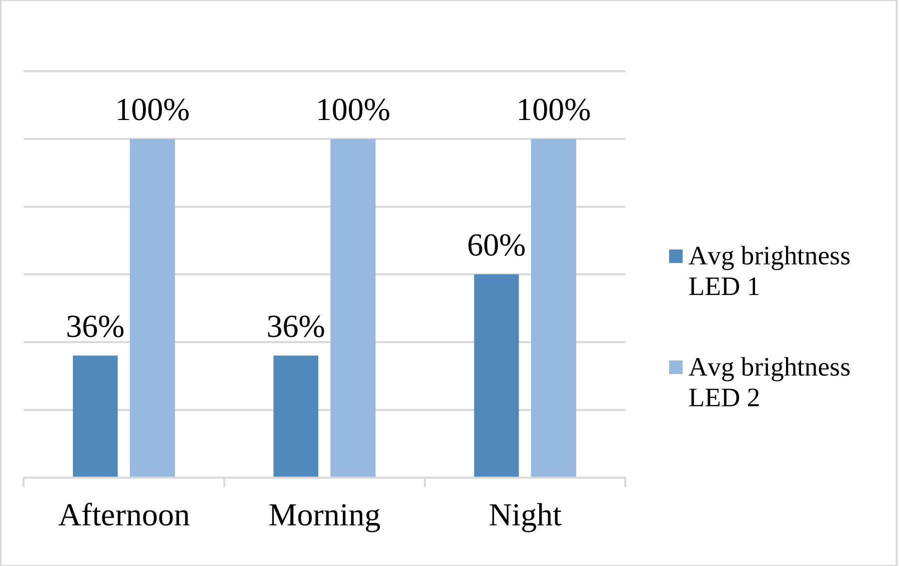

Figure 8: Average LED brightness of SVM-based lighting control system at different times.

Model Performance comparison at different times of the day

Table 6: Comparison of Model Performance During Morning Hours

	DTR	SVM	FFNN	LR
Motion sensor readings	1	1	1	1
Light sensor readings	0.6	0	0.7	0.7
Predicted light intensity	0.6	1	1	0.5

The Linear Regression-based model perfomed best keeping the average LED brightness at 50% during morning hours when occupancy was detected.

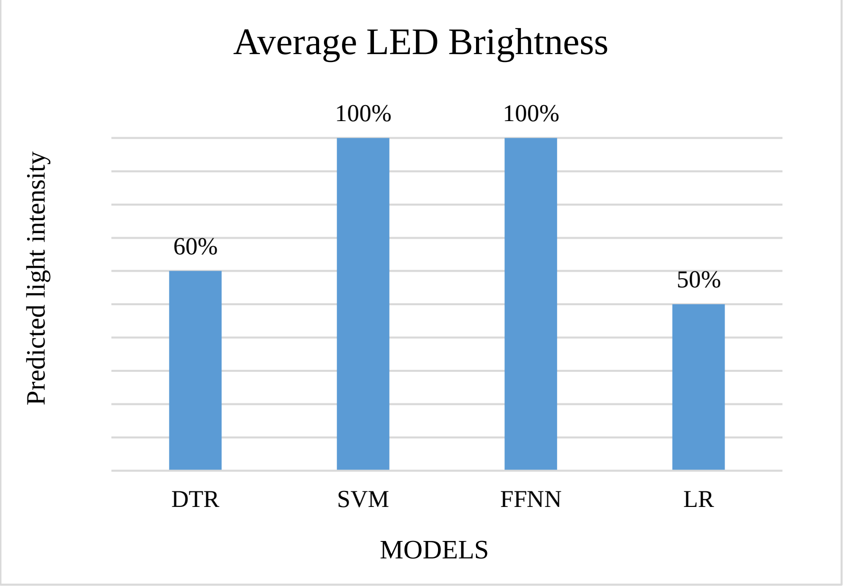

Figure 9: Average LED brightness predicted by each model during morning hours

Table 7: Comparison of Model Performance During Afternoon Hours

	DTR	SVM	FFNN	LR
Motion sensor readings	1	1	1	1
Light sensor readings	0.8	0.2	0.5	0.9
Predicted light intensity	0.4	1	1	0.0

The Linear Regression-based model perfomed best keeping the average LED brightness at 0% during afternoon hours when occupancy was detected.

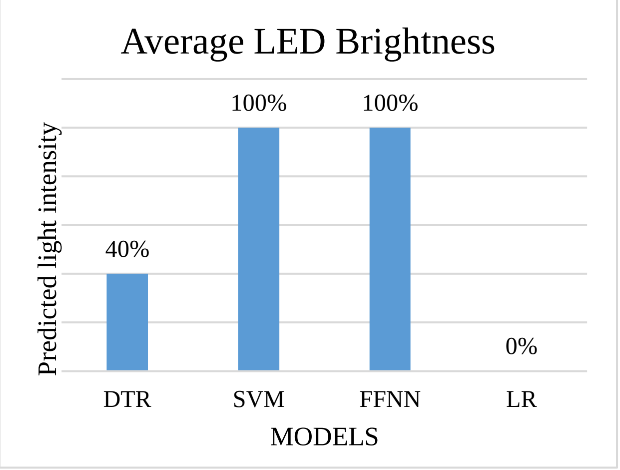

Figure 10: Average LED brightness predicted by each model during afternoon hours

Table 8: Comparison of Model Performance During Night Hours

	DTR	SVM	FFNN	LR
Motion sensor readings	0	0	0	0
Light sensor readings	0	0	0	0
Predicted light intensity	0	1	1	0.2

The Decision Tree Regressor model performed better during the night hours but overall did not outperform the Linear Regression Model

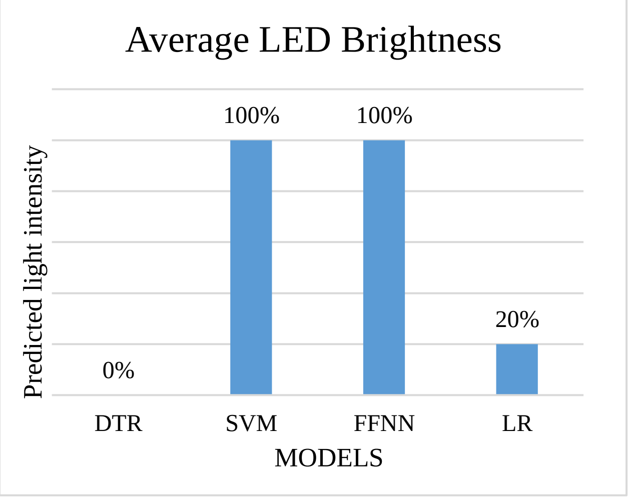

Figure 11: Average LED brightness predicted by each model during night hours

CONCLUSION

In this project, a smart lighting system was designed and implemented for a hospital building. This system uses advanced technologies like machine learning and neural networks to make decisions. It also uses IoT technology to keep track of how bright the surroundings are, detect when rooms are occupied, and adjust the lighting accordingly. Originally, the main goal was to create a controller using neural networks. However, it was realized that a different kind of controller using machine learning worked better when evaluated using mean square error. This change in direction happened because of the specific data gotten, showing that a different approach could give better results. As for the intensity captured by the light sensor, the predictions were actually done, there are varying values presented in the results of DTR and LR while that of SVM and FFNN were constant which is evidence of how poorly the algorithms perform on this task, they are not good fit for this task. The predicted intensity of the light should be low in morning, afternoon and at night, since the goal of this research is to achieve low light intensity across the different times of the day because it would lead to better energy savings. The wide variance and negative value of the R2 score suggests that it is not valid metric of comparison in the context of this research, given the nature of the data set. Some other valid metrics of comparison that should be considered is the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE). The system designed here can be upscaled and deployed for use in hospital buildings, offices, residential areas, and other indoor areas.

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