Journal Homepage: - www.journalijar.com

INTERNATIONAL JOURNAL OF ADVANCED RESEARCH (IJAR)

Article DOI: 10.21474/IJAR01/22212
DOI URL: http://dx.doi.org/10.21474/IJAR01/22212

ISSN NO. 2320-5407

RESEARCH ARTICLE

INTELLIGENT HOME AUTOMATION USING MACHINE LEARNING AND VOICE CONTROL

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Manuscript Info

Manuscript History
Received: 04 September 2025
Final Accepted: 06 October 2025
Published: November 2025

Key words:-
Machine Learning, IoT, Linear Regression, Voice Control, Smart Home, Energy Efficiency, Google Assistant, NodeMCU, Automation, Cloud Integration.

Abstract

The Machine Learning–Enabled Voice Controlled Home Automation System is another smart automation solution designed to automate and optimize household lighting and appli- ance control not only with voice commands but also predictive in- telligence. The system integrates voice commands through Google Assistant–based voice control with machine learning algorithms for enhancing convenience, energy efficiency, and user adapt- ability. Users can control the devices (like lights, fans, and other electrical appliances) through voice, which gets processed via Google Assistant and will be forwarded to NodeMCU (ESP8266) microcontroller connected to relay modules. In parallel, a Linear Regression model does prediction for lighting devices' ON/OFF timing history-gHall Light, Room Light, and Lawn/Gate Light-to find out the activation/kill times in the future. It thus facilitates automatic adjustment of lighting schedules according to usage behavior and saves a lot of energy with smart scheduling. The system operates on manual, voice, and automated controls to make it accessible to all users, including older persons and differently-abled people. In general, the project depicts how IoT, cloud connectivity, and machine learning together transform traditional home systems into smart, adaptive, and sustainable smart environments..

Introduction:-

The integration of Internet of Things (IoT), Artificial In- telligence (AI), and Machine Learning (ML) technologies in recent times has significantly transformed how people interact with their living environment [1]. The proposed Machine Learning–Enabled Voice Controlled Smart Home Automation System provides a voice-assisted, data-driven solution that enhances comfort, convenience, and energy efficiency by en- abling predictively automated smart homes. Traditional home control methods rely on manual switches or fixed schedules that cannot respond to dynamic user behavior or energy usage patterns [2]. The proposed system overcomes these limitations by utilizing real-time voice control through Google Assistant and machine learning algorithms to predict light ON/OFF timings based on historical usage data and duration [3]. The system employs NodeMCU ESP8266 as the pri- mary microcontroller, interfaced with relay modules to con- trol various household appliances such as lights and fans. Voice commands issued through Google Assistant are pro- cessed and transmitted via Sinric Pro or similar IoT cloud platforms, enabling instantaneous execution of actions by the microcontroller [4]. Historical lighting data for multiple zones—including hall, room, and lawn/gate—are analyzed using a Linear Regression–based predictive model to estimate future activation and deactivation times. This multi-mode system, combining manual, voice-controlled, and machine learning–based operations, enhances accessibility for elderly and differently-abled individuals while reducing energy wastage. By integrating IoT connectivity, cloud computing, and data intelligence, the project demon- strates how modern smart home systems can evolve from reactive automation to proactive, adaptive, and sustainable living environments [5].

Literature Survey:-

The combination of Internet of Things (IoT) and Machine Learning (ML) technologies has greatly advanced smart home automation, particularly in the domains of energy optimization and intelligent control [1], [6]. Numerous researchers have been drawn to data-driven and voice-assisted systems aimed at improving user comfort, accessibility, and energy consumption efficiency. R. Kumar, V. Singh, and A. Sharma [7] prescribed regression-based models to forecast household energy con- sumption patterns, demonstrating how statistical learning can accurately predict power usage trends. Similarly, Wei Li and Hui Zhao [8] developed a time-series forecasting approach for appliance usage prediction, where adaptive learning reduced unnecessary energy consumption. A. Rahman, M. Khan, and R. Sultana [9] proposed a hybrid IoT–AI framework for real- time monitoring and predictive control, enabling appliances to respond autonomously to detected user behavior. These studies form the foundation for light pattern prediction and automated control systems. Complementing these efforts, several researchers have ex- plored IoT-driven, voice-controlled automation. K. Vanitha, P. Kumar, and R. Devi [10] developed a Google Assistant–based home automation system integrated with switching circuits, Wi-Fi connectivity, and sensor feedback for flexible operation through the Blynk mobile application. Similarly, S. Koustubh Sanjay Masavekar, A.

Pawar, and D. Kadam [11] discussed smart homes built upon wireless technologies such as Wi-Fi, GSM, and Bluetooth, enabling centralized control of lighting and appliances through a NodeMCU microcontroller. Further, Sanjiv S. Paul, N. Mehta, and A. Gupta [12] and Harsha Vardhan Reddy, S. Kumar, and D. Priya [13] proposed IoT-based voice recognition systems capable of remotely oper- ating multiple appliances in real time. Their designs integrated sensors such as PIR, temperature, gas (MQ2), and LDR to improve energy efficiency and environmental adaptability. These studies collectively emphasize how IoT and voice- control frameworks enhance convenience and accessibility, particularly for elderly and differently-abled users. In another contribution, Muhammad Abbas Khan, Rehan Ali, and Hamza Qureshi [14] utilized Raspberry Pi and ESP8285 microcontrollers to propose a smartphone-based home automation platform that demonstrates scalability and user-friendliness in IoT-enabled environments. Similarly, E.

Mahesh Babu, V. Rao, and A. Ghosh [15] presented a low-cost, ESP32-based automation system that supports both online and offline modes through the Blynk application, enabling control of multiple relays. N. Bansal, M. Thomas, and K. Reddy [16] proposed a voice-controlled home automation system that prioritizes energy efficiency and ease of use through smart communication protocols. Finally, K. R. Singh and M. Thomas [17] introduced a Bluetooth-based automation system that enables users to operate appliances via Android mobile applications, enhancing accessibility for physically challenged users. While these systems successfully integrate IoT connectivity, voice control, and remote accessibility, most still operate on reactive automation, relying solely on user commands without adaptive intelligence. In contrast, the system proposed in this work integrates voice-controlled IoT automation with machine learning–based light pattern prediction, enabling the system to learn user behavior and automatically schedule lighting based on historical patterns. This hybrid modeling approach bridges the gap between manual/voice operation and predictive autonomous control, resulting in a more intelligent, energy- efficient, and context-aware smart home environment [5].

Proposed Methodology:-

The proposed system is designed to develop an integrated IoT- and Machine Learning–based voice-controlled home au- tomation framework that will enable users to switch on/off and manage appliances manually, through voice commands, and via intelligent prediction. This system amplifies convenience, accessibility, and energy efficiency within modern homes by integrating cloud-based voice recognition with data-driven pre- dictive modeling. The block diagram of proposed methodology is shown in figure 1.

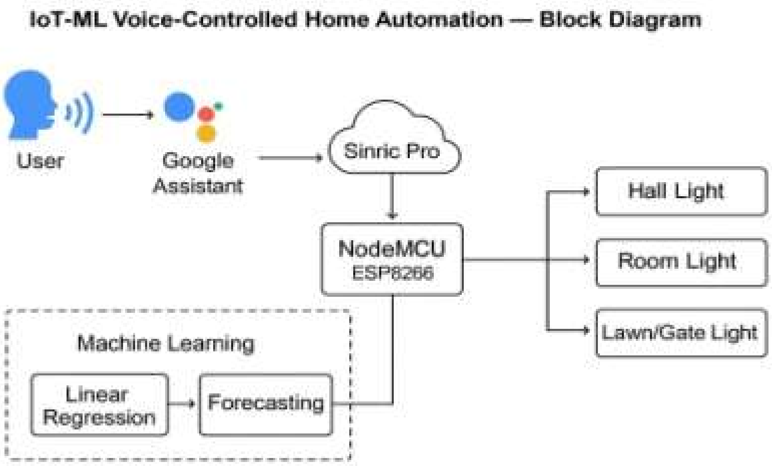

Fig. 1. Block Diagram

It uses a NodeMCU microcontroller, ESP8266, at its core hardware level, the internet being provided by Wi-Fi. Com- munication is done with a Sinric Pro cloud platform, which, through Google Assistant, interprets voice commands from users. It works this way: a user speaks, ”Turn on the Hall Light” or ”Switch off the Fan,” and Google Assistant interprets this, sending it to NodeMCU via the Sinric Pro server. The NodeMCU triggers on/off through relay modules, basically electronic switches to the respective device. Thus, using only his voice or a smartphone-based manual input, any layman can control appliances in real time. The system will also work for an aged or differently-abled person. This system integrates an ML component, besides simple reactive control, which learns the usage pattern of lighting and predictively advises. Data were generated for a synthetic dataset representing 30 days of the operation of lights for Hall Light, Room Light, and Lawn/Gate Light. Each record includes the following: ON and OFF times, and duration of light ON. The above data are used to train Linear Regression models, which predict each day’s expected hour of the next day for each type of light. Features:

NodeMCU ESP8266:-

The NodeMCU ESP8266 is an open-source, Wi-Fi-enabled microcontroller that comes in a compact form. Therefore, this will allow any IoT projects to function immediately. A microcontroller with an integrated TCP/IP protocol stack enables it to communicate with the cloud directly. Fig 5: NodeMCU ESP8266 LightCode(encodednumerically)andDurationhrsasprimarypreTdhicetoNrosd. eMCU has several GPIOs, an analog input, and it The models were then evaluated after training using MAE and gave very good accuracy, with less than one hour average deviation between predicted and actual values. These are then used to automatically provide the adjustment of lighting schedules by the system itself in a way that will reduce energy wastage and optimize operation times without any extra sensors. The hybrid design will allow IoT-based control and ML-based prediction, thus making the system flexible, scalable, and efficient. While users could manage appliances manually or through voice commands, they might allow the system to automatically schedule operation activities learned through usage patterns. Overall, this paper will show how the integration of IoT, cloud computing, and machine learning will turn a traditional home automation into an proactive, intelligent and energy-conscience smart home environment.

System Design and Components Used:-

Machine Learning–Enabled Voice Controlled Smart Home Automation System will provide reactive appliances control: voice/manual and predictive: automated. The proposed system is designed to intelligently manage lighting and household devices with NodeMCU (ESP8266), relay modules, and cloud services like Google Assistant and Sinric Pro. The overall circuit design has NodeMCU connected to relay modules for acting like an electronic switch for high- voltage electrical appliances such as lights, fans, and garden lighting. When any user provides a voice command via Google Assistant, the command is processed via the Sinric Pro cloud server and sent back to NodeMCU through Wi-Fi. NodeMCU interprets the command and triggers the respective relay, thus turning the appliance ON or OFF instantly. Besides voice and manual controls, the system also has a machine learning module, whose training is done using Linear Regression models to predict light ON and OFF times accord- ing to prevailing historical usage. The automatically computed predictions on lighting operational timing enable the system to automatically schedule the lighting operation—much-needed energy-saving with enhanced comfort without the user's con- tinuous interference. Integration of ML at home makes it intelligent; it anticipates the needs of the user and optimizes power consumption. Lab prototyping will be done on a breadboard using jumper wires, wherein resistors will be used for current stability to avoid burns in a circuit. A regulated power supply powers the NodeMCU and relay modules for better operation. The full setup will support manual overdrive, voice, and prediction- based automation for flexibility, accessibility, and energy effi- ciency. also supports SPI, I2C, and UART communication protocols, hence it can easily connect with all types of sensors, relays, and output devices. For this system, the NodeMCU acts as the central control unit that not only processes voice commands through the Sinric Pro cloud interface but also runs machine learning–based prediction algorithms for automatic schedul- ing. Its ease of programming using the Arduino IDE, its low price, and its wireless connectivity make it efficient for IoT automation in real time

Google Assistant:-
Google Assistant is a voice-based assistant using cloud recognition and artificial intelligence that enables the user to make enabled actions or devices. For this project, it is the user interface—the user tells it, ”Turn on the Hall Light” or ”Switch off the Lawn Light.” This tells the Sinric Pro server, and in turn, the NodeMCU via Wi-Fi. Google Assistant is providing the right voice recognition with real-time response, and this system will definitely enable hands-free control over home automation.

Sinric Pro:-
In general, Sinric Pro represents an IoT cloud platform that provides the possibility for both voice assistants (Google Assistant and Amazon Alexa) to connect to IoT hardware. This is a connection bridge between the user's voice commands and the NodeMCU. In case Google Assistant recognizes some command, it sends it securely via Sinric Pro to NodeMCU, which then performs the action. Apart from voice command handling, Sinric Pro supports Real Time Synchronization, Remote Access, and Event log- ging to monitor/control appliances using a smartphone, thus ensuring nonstop operation and scaling in smart home envi- ronments.

Arduino IDE:-
The Arduino Integrated Development Environment is the platform from where this module, NodeMCU ESP8266, can be programmed. It allows writing, compiling, and uploading the control code used for managing the operations of a relay, voice command responses, and communication with cloud platforms. This is also flexible and user-friendly, with many IoT and machine learning libraries. In this setup, the Arduino IDE does code development on Google Assistant integration, Sinric Pro connectivity, and handling machine learning pre- diction data to effectively coordinate hardware and software interaction.

Methodology and Workflow:-
The System methodology of the proposed Machine Learn- ing–Enabled Voice Controlled Smart Home Automation Sys- tem incorporates IoT-based voice/manual control, as well as machine learning–based prediction automation, to achieve intelligent, energy-efficient, and user-friendly home manage- ment. The workflow is designed to enable users to operate appliances instantly through Google Assistant while also al- lowing the system to learn from historical usage data and predict future lighting schedules automatically. The first phase of IoT voice control involves real-time features that include the following: asking the user to con- verse with the system through Google Assistant using nat- ural language like ”Turn on the Hall Light” or ”Switch off the Fan.”

These are processes from the cloud via Google Assistant and further sent through the Sinric Pro platform, which connects the user interface and the IoT hardware for communication. This gets the respective relay module on or off through a processed instruction received by the NodeMCU (ESP8266) microcontroller connected via Wi-Fi. Thereafter, this will switch the connected appliance either ON or OFF as required. Thus, real-time operation carries with it fast responsiveness, remote access, and ease, especially to old or physically challenged people who get hands-free control. The next stage brings in predictive automation based on machine learning, whereby the system intelligently schedules light operations without the intervention of a user. The work flow of the proposed method is shown in figure 5. A synthetic dataset was developed for a period of 30 days over three lighting categories: Hall Light, Room Light, and Lawn/Gate Light were shown in figure 2,3 and 4.

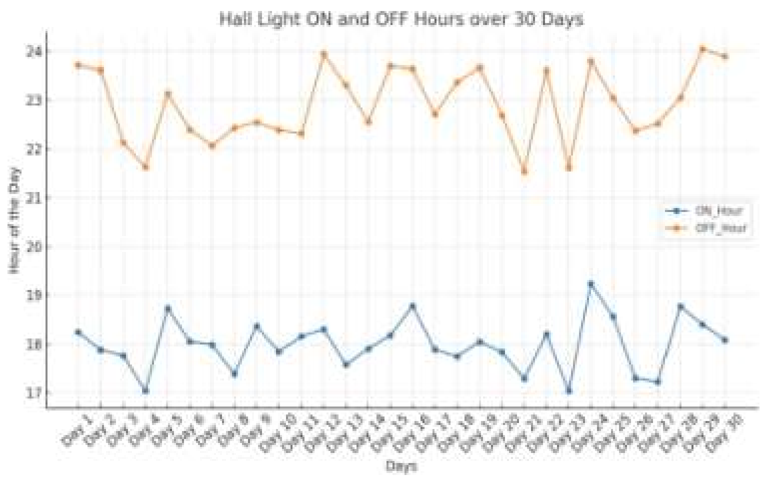

Fig. 2. Hall Light Operation Pattern

Every record maintained the ON and OFF time, usage duration, and light type. Data preprocessing was done to encode light types numerically and use duration as a key input feature. Using this dataset, two Linear Regression models were built: one for the prediction of ON time and another for the prediction of OFF time. The models were trained and tested using Mean Absolute Error (MAE) as the metric for performance evaluation and result accuracy less than a one- hour average deviation. Trained models predict the lighting schedule for the next day, with ON and OFF hours included for each category. Predictions must be stored and may be passed to NodeMCU for the automation of appliances at optimal times in order to conserve energy and increase operational efficiency.

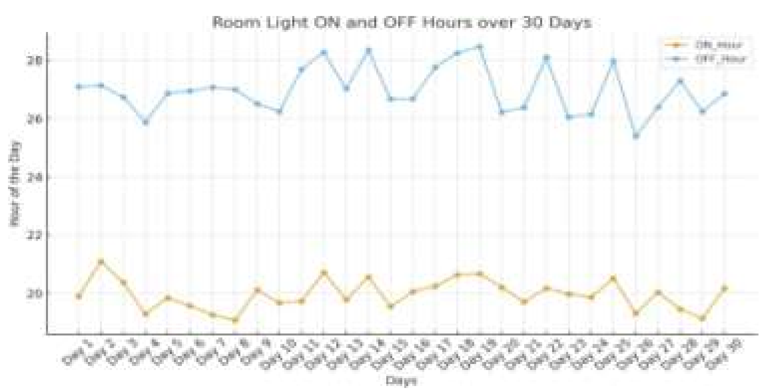

Fig. 3. Room Light Operation Pattern

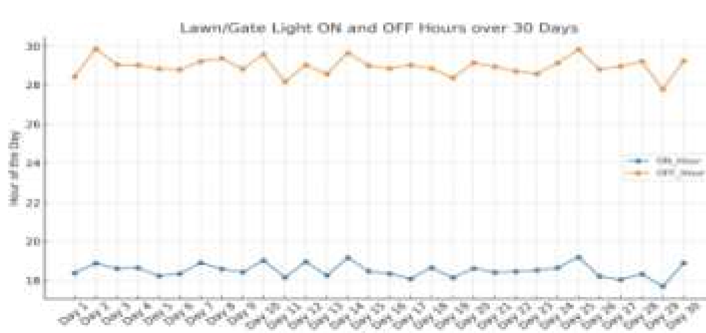

Fig. 4. Lawn Light Operation Pattern

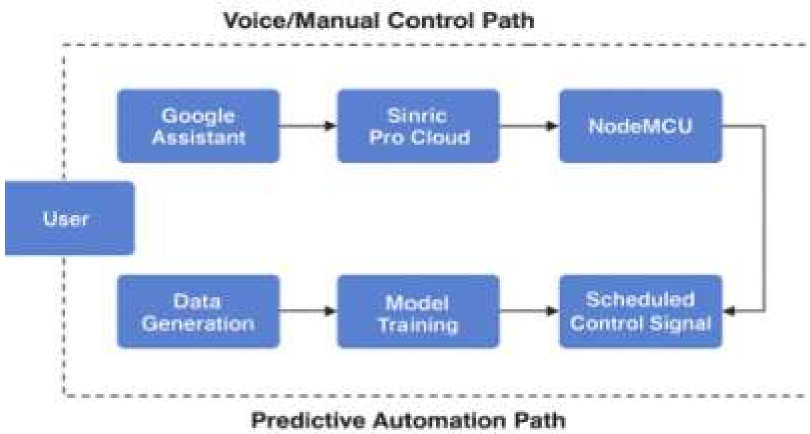

Fig. 5. Work Flow

The integrated workflow includes both voice/manual con- trol and predictive scheduling is shown in figure 5. In the voice control path, commands flow from the user to Google Assistant, through the Sinric Pro cloud, to the NodeMCU, which activates the relay modules and controls the appliances. In the predictive automation path, data generation is done, it undergoes processing through machine learning models, and scheduled control signals are converted to go into NodeMCU for automated operation. This ensures real-time responsiveness in the case of either manual or voice-based operation and autonomous decisions through predictive learning. It basically sums up the whole workflow: hybridity of the system—pretty flexible, adaptable, and energy-efficient. Integration of cloud computing with IoT connectivity and data intelligence will turn what was conventionally a home automation setup into a self-learning smart home ecosystem capable of proactive and sustainable operation.

Table I Performance Of Linear Regression Models For Light Operation Prediction

Light Type	Pred. ON (hrs)	Pred. ON (hh:mm)	Pred. OFF (hrs)	MAE (hrs)
Hall Light	18.2	6:12 PM	23.43	0.8
Room Light	20.1	8:06 PM	2.03	0.8
Lawn/Gate Light	18.7	6:42 PM	4.76	0.8
OFF Time Model MAE				0.9

Table Ii Performance Of Iot-Based Light Control System

Parameter	Value	Remarks		
Avg. Voice Response Time	< 1.5 s	Google	Assistant	to
		NodeMCU		

Results and Performance Analysis:-

Communication Protocol Wi-Fi (Sinric Pro) Reliable connectivity The developed and tested Machine Learning–Enabled Voice Controlled Smart Home Automation System evaluated its predictive performance along with real-time operational ef- ficiency. Here, the results show that the incorporation of machine learning algorithms together with IoT-based voice control significantly enhances automation accuracy, respon- siveness, and energy efficiency within a smart home environ- ment. In the machine learning module, it was considered necessary to train and test models on a synthesized dataset of light usage data for three categories—Hall Light, Room Light, and Lawn/Gate Light—for a period of 30 days. The parameters involved in this dataset are light type, ON time, OFF time, and duration of operation. Further, two Linear Regression models were separately trained to predict both ON and OFF times. For these models, Mean Absolute Error (MAE) was used, which calculates the average deviation of predictions from actual values. Accordingly, an ON-time prediction model gave a very good approximation with an MAE of approximately 0.8 hours, while in the case of the OFF-time prediction model, the MAE was 0.9 hours, thus establishing a high degree of accuracy in forecasting light operation schedules.

The ON times predicted are: 18.2 hours (6:12 PM) for Hall Light, 20.1 hours (8:06 PM) for Room Light, and 18.7 hours (6:42 PM) for Lawn/Gate Light, respectively, rather close to the expected realistic life values. Correspondingly, the predicted OFF times also showed quite good approximations to the actual patterns of this kind. This shows that the different models had learned the temporal behavior of various lighting ambiance effectively. These have been successfully stored in a CSV format and integrated into the IoT layer to get the automation schedule. The real-time test was conducted in the IoT control module to validate the voice-controlled and manual operations of the features. In real-time, the system responded to what was told in less than 1.5 seconds from the moment the voice command was uttered, through Google Assistant, Sinric Pro, to NodeMCU; being online on Wi-Fi and accurate triggering of the relay have been consistently reliable.

It also allowed access to smartphone applications for users to control appliances remotely.Control Accuracy 100% A ccurate relay operation Smartphone App Control Enabled Remote control verified This integrated model was the marriage between IoT au- tomation and machine learning prediction, reaping a dual advantage. If voice control enables immediate manual inter- action, predictive scheduling reduces the need for continuous user input, optimizing energy and automating efficiency. The hybrid model allowed operating the system in interactive and autonomous modes based on user preference and availability. Overall, the results in table I and II also confirm that the proposed system is not only able to accurately predict light patterns but also can perform reliably in real-time IoT en- vironments. Combining predictive analytics with cloud-based automation lays a very good foundation for smart home systems that are adaptive and data-driven. This successful implementation underlines how the intersection of machine learning, IoT, and cloud computing can favorably create intel- ligent, sustainable, and user-centered automation frameworks for modern living.

Advantages and Limitations:-

Different aspects make the Machine Learning–Enabled Voice Controlled Smart Home Automation System quite effective in maximizing convenience, accessibility, and energy efficiency in the modern home. This includes a hybrid control functionality that offers manual, voice-based, and machine learning–driven automatic operation modes. The system allows users to interact with it in multiple ways, ensuring flexibility and ease of use for people of all ages, including the elderly and differently abled. The machine learning models predict light ON and OFF times, enabling proactive appliance scheduling and minimizing unnecessary power consumption for sustain- able energy use. The system shows real-time responsiveness through seam- less integration of Google Assistant, Sinric Pro, and NodeMCU (ESP8266), achieving a latency of less than 1.5 seconds between command input and appliance response. Its design is cost-effective and scalable, as it relies on affordable components like NodeMCU and relay modules, making it suitable for both small and large smart home setups. Its modular design allows easy expansion with new appliances or sensors.

In terms of accessibility, Google Assistant enables intuitive voice control, while Sinric Pro provides smartphone-based remote access, letting users monitor and control appli- ances from anywhere. With data-driven automation, the system learns from user behavior over time, transforming traditional reactive control into intelligent, self-learning automation. However, despite these advantages, the system has some limitations that could be improved in future versions. The most significant challenge is its dependence on internet connectivity, since both Google Assistant and Sinric Pro rely on cloud-based communication. Any disruption in the network may lead to delays or temporary unavailability. Additionally, the machine learning module currently uses synthetic data for training, which, while effective for testing, may not fully capture real- world usage behavior. Incorporating real-time sensor data would increase accuracy and reliability. Another limitation lies in the Linear Regression model, which works well for simple time-based predictions but struggles with complex or nonlinear behavior. Using advanced models like neural networks or ensemble methods could enhance prediction precision. From a hardware perspective, the NodeMCU has lim- ited processing power and memory, which restricts scal- ability when managing multiple appliances simultaneously.

This could be resolved by upgrading to more powerful IoT controllers or adopting distributed microcontroller networks. Finally, the absence of real-time environmental sensors—such as motion, temperature, or light intensity sensors—prevents dynamic adjustments based on room conditions or occupancy. Adding such sensors would make the system more context- aware and further improve energy optimization. Despite these limitations, the system effectively showcases how combining IoT, machine learning, and cloud computing can revolutionize home automation. Its hybrid nature bridges the gap between traditional reactive systems and intelligent, adaptive environments, paving the way for the next generation of self-learning, energy-efficient smart homes.

Future Scope:-

The proposed Machine Learning–Enabled Voice Controlled Smart Home Automation System lays a strong foundation for creating intelligent, accessible, and energy-efficient living spaces. However, there are several opportunities to further enhance its performance, adaptability, and scalability in the future. With the integration of emerging technologies and thoughtful design improvements, the system can evolve from a cloud-dependent model into a fully autonomous and context- aware smart home ecosystem. One promising direction is the integration of real-time environmental sensors. By adding sensors such as PIR (motion sensors), LDR (light-dependent resistors), and temperature or humidity sensors, the system can react dynamically to occupancy, daylight, and ambient conditions. This would allow appliances and lighting to operate only when needed, im- proving both energy efficiency and user comfort. Additionally, incorporating IoT-based data logging would enable continuous collection of real-world data, replacing synthetic datasets. This real data could be used to periodically retrain the machine learning models, making predictions more accurate and adapt- able over time. Another significant improvement lies in advancing the AI and machine learning capabilities of the system. While the cur- rent Linear Regression model provides accurate predictions, it can be upgraded with more sophisticated algorithms such as Random Forests, Gradient Boosting, or Artificial Neural Networks to better understand complex behavioral and nonlin- ear patterns.

Furthermore, exploring Reinforcement Learning (RL) could make the system truly adaptive, enabling it to learn optimal energy usage and lighting strategies from continuous feedback based on user interaction and environmental factors. This would transform it from a simple predictive model into a self-optimizing automation system. The adoption of Edge AI presents another powerful en- hancement. By deploying lightweight machine learning mod- els directly on edge devices like ESP32 or Raspberry Pi, the system could process data locally instead of relying entirely on cloud servers. This approach would reduce latency, minimize cloud dependency, enhance data privacy, and maintain system functionality even during internet outages. From a scalability standpoint, the system could evolve to support distributed IoT networks and multi-controller coor- dination for managing larger homes, offices, or commercial buildings. Integration with renewable energy sources such as solar panels could enable predictive scheduling based on en- ergy availability, further promoting sustainability. Developing a graphical dashboard or mobile app would also help users visualize energy consumption, monitor system status, and view predictive insights in real time. In terms of security and privacy, future versions can in- clude stronger measures like end-to-end encryption, multi- factor authentication, and local data storage to ensure safe communication between devices and protect the system from unauthorized access

Conclusion:-

The proposed Machine Learning–Enabled Voice Controlled Smart Home Automation System effectively demonstrates how the combination of the Internet of Things (IoT), cloud com- puting, and machine learning can transform traditional home automation into a more intelligent and efficient experience. By integrating voice-based control with predictive intelligence, the system provides a hybrid solution that enhances convenience, accessibility, and energy efficiency in modern households. Through platforms like Google Assistant and Sinric Pro, users can manage their home appliances in real time using simple voice commands, while the machine learning component en- ables the system to autonomously predict and schedule lighting operations based on previous usage patterns.

The system achieves highly accurate light operation predic- tions, with a Mean Absolute Error (MAE) of less than one hour, proving the reliability of linear regression models for behavioral forecasting. Its IoT-based architecture ensures real- time responsiveness and remote accessibility, giving users the freedom to control appliances from anywhere. The inclusion of manual, voice, and automated operation modes also ensures ease of use for a wide range of users, including the elderly and differently-abled, promoting inclusivity and comfort. Moreover, the project highlights how data-driven automa- tion can contribute to sustainable living by improving energy management and resource efficiency. By learning user habits and optimizing operation schedules, the system reduces unnec- essary power consumption without compromising comfort or usability. Its low-cost, modular hardware design, built around NodeMCU (ESP8266) and relay modules, makes it not only affordable but also easily scalable for real-world applications.

In essence, this work represents a meaningful step toward . creating intelligent, adaptive, and self-learning smart home ecosystems. With future enhancements—such as integrating real-time environmental sensors, advanced AI algorithms, and edge computing—the system can evolve into a more autonomous, responsive, and sustainable home automation framework. The successful combination of machine learning prediction with voice-controlled IoT architecture sets a strong foundation for next-generation smart homes that are aware, predictive, and energy-conscious, paving the way for a future of truly intelligent and connected living environments.

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