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Interpretable Deep Neural Networks using SHAP And LIME for Decision Making in Smart Home Automation

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Abstract - Deep Neural Networks (DNNs) are increasingly being used in smart home automation for intelligent decision-making based on IoT sensor data. This project aims to develop an interpretable deep neural network model for decision-making in smart home automation using SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations). The focus is on enhancing transparency in AI-driven automation systems by providing clear explanations for model predictions. The approach involves collecting IoT sensor data from smart home environments, training a deep learning model to recognize patterns and make automation decisions, and applying SHAP and LIME to interpret its outputs. This will help homeowners and system developers understand why certain actions are triggered, increasing trust and reliability in AI-powered automation.

Key Words: Interpretable AI, Deep Learning, SHAP, LIME, Smart Home Automation, IoT, Explainability, Sensor Data, Decision Support Systems.

1. INTRODUCTION

The goal of this project is to create a Deep Neural Network (DNN) for smart home automation that facilitates intelligent decision-making through user behavior and environmental data. One of the main areas of focus is on improving transparency in deep learning-based systems through clear and explainable explanations for AI-driven behavior. By incorporating interpretability tools such as SHAP and LIME, the system can explain its choices, for instance, switching lights off or temperature adjustments, to users in a manner that makes sense to them. This does not only generate user trust but also facilitates responsible AI practices since it makes the technology more transparent and easier to understand. The project's scope goes further than automation to encompass ethics and legality, seeking to enhance real-world applicability in applications such as energy saving, security, and elderly care. By making AI explainable, the system guarantees users are informed of the rationale for each automated activity, hence ensuring transparency and accountability. Finally, the objective is to build a smart home environment that not only has intelligence but is also secure, energy-efficient, and comfortable so that AI-based decisions become user-friendly and based on human values.

2. LITERATURE REVIEW

Divyani Sen, Bharat Singh Deora, Arun Vaishnav [1]:
This research introduced a blended approach that leverages SHAP and LIME alongside LSTM networks to enhance the interpretability of deep learning in time-series analysis. By applying SHAP for global feature importance and LIME for individual prediction explanations, the framework provided deeper insights into how time-dependent variables like humidity and temperature affect energy consumption predictions. The study emphasizes the necessity of transparent models to build user trust in smart home energy systems.

Jiayi Kuang, Gang Xue, Zeming Yan and Jing Liu [2]:
The authors developed a framework for automatically generating smart home automation scripts using natural language processing and logic-based models. Although the study did not focus on model interpretability tools, it contributed significantly by proposing a user-friendly interface that simplifies the creation and execution of automation logic. This supports the broader objective of making smart home AI systems more understandable and accessible to end users.

Yu-Hsiu Lin, Huei-Sheng Tang, Ting-Yu Shen, and Chih-Hsien Hsia [3]:
This paper introduced a smart energy management system utilizing deep learning techniques, specifically LSTM and MLP models, for time-series load prediction. While the core emphasis was on forecasting and non-intrusive monitoring, the authors acknowledged the importance of incorporating explainability mechanisms to interpret usage patterns and user behavior. Their work suggests a growing need for integrating methods like SHAP and LIME to support interpretability in energy-focused AI applications.

Alexander Orlowski and Wulf Loh [4]:
This study explored issues surrounding data privacy and user control in AI-powered smart homes. It proposed a meta-assistant to enable residents to manage personal data flows effectively. The authors emphasized the ethical implications of opaque AI models and advocated for systems that not only safeguard privacy but also explain their operations clearly—particularly when these systems are responsible for sensitive decision-making.

Chitukula Sanjay, Konda Jahnavi and Shyam Karanth1[5]:
The authors presented a secure automation system that uses convolutional neural networks to detect human motion and classify potential threats. Although interpretability tools were not applied in this model, the research highlights the importance of integrating such tools in future work. Enhancing transparency in security decisions could improve user confidence and make AI-based surveillance systems more reliable and auditable.

Heetae Yang, Wonji Lee, and Hwansoo Lee [6]:
This study investigated user preferences regarding automation in smart homes, revealing that perceived controllability and transparency influence adoption. The authors advocated for adaptive and explainable systems, arguing that tailoring automation to user characteristics is essential for fostering trust in AI technologies within domestic settings.

Murad Khan, Bhagya Nathali Silva, and Kijun Han [7]:
The authors proposed an IoT-based energy-aware smart home system using ZigBee to reduce interference and improve energy efficiency. Though the system effectively managed resources, it lacked decision transparency. This paper highlighted an opportunity for integrating explainable AI techniques like SHAP and LIME to provide clarity in automated energy decisions.

Vamsikrishna Patchava, Hari Babu Kandala and P Ravi Babu [8]:
This research designed a home automation system using Raspberry Pi and Computer Vision for real-time monitoring and motion detection. The system supports IoT-based remote control, but the authors did not incorporate any interpretability features, suggesting a potential enhancement by applying explainable AI to better contextualize surveillance decisions.

Majid Al-Kuwari, Abdulrhman Ramadan, Yousef Ismael, Laith Al-Sughair and Adel Gastli [9]:
This paper presented an IoT-driven smart home monitoring platform using NodeMCU and EmonCMS to track environmental factors such as temperature, humidity, and air quality. While the platform offered efficient sensing and remote control, the authors did not implement model interpretability, identifying a clear gap where SHAP and LIME could contribute to explainable decision-making.

Leandro Filipe, Ricardo Silva Peres and Rui Manuel Tavares[10]:
This study introduced a voice-activated smart home controller that uses online machine learning to adapt to user behavior in real time. The system was designed to operate without continuous internet access, allowing local execution and learning. It was validated through a motorized blinds control setup, demonstrating that adaptive learning improved personalization and responsiveness. The research highlights the value of incorporating intelligent, user-driven automation in smart home s

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3.Comparsion Table

S. No	Title	Author's	Methodology Used	Findings from the Reference Paper
1	Divyani Sen, Bharat Singh Deora, Arun Vaishnav (2025).	Explainable Deep Learning for Time Series Analysis: Integrating SHAP and LIME in LSTM-Based Models	Combined LSTM forecasting with SHAP for global insights and LIME for localized explanations	The study demonstrated that merging SHAP and LIME improved understanding of time-dependent features, boosting model transparency.
2	Jiayi Kuang, Gang Xue, Zeming Yan and Jing Liu (2023)	An Automation Script Generation Technique for the Smart Home	Utilized NLP and logical translation to automate script creation for smart home environments	Offered a simplified approach to configuring home automation logic, enhancing accessibility and clarity for non-programmers.
3	Yu-Hsiu Lin, Huei-Sheng Tang, Ting-Yu Shen, and Chih-Hsien Hsia (2022)	A Smart Home Energy Management System Utilizing Neurocomputing-Based Time-Series Load Modeling and Forecasting Facilitated by Energy Decomposition	Applied neurocomputing with LSTM and MLP for energy forecasting and behavioural analysis	Provided effective load predictions and outlined the importance of integrating explainability for user behavior insights..
4	Alexander Orlowski and Wulf Loh (2025)	Data Autonomy and Privacy in the Smart Home: The Case for a Privacy Smart Home Meta-Assistant	Data Autonomy and Privacy in the Smart Home: The Case for a Privacy Smart Home Meta-Assistant	Data Autonomy and Privacy in the Smart Home: The Case for a Privacy Smart Home Meta-Assistant
5	Chitukula Sanjay, Konda Jahnavi and Shyam Karanth(2024)	A Secured Deep Learning-Based Smart Home Automation System	Used CNNs for detecting and classifying suspicious activities using visual input	Achieved high accuracy in intrusion detection; suggested interpretability as a future enhancement for user trust.
6	Heetae Yang, Wonji Lee, and Hwansoo (2018)	IoT Smart Home Adoption – The Importance of Proper Level Automation	Conducted empirical analysis on automation preferences in smart home users	Found that adaptive, transparent systems were more likely to be accepted by users, supporting interpretable design..
7	Murad Khan, Bhagya Nathali Silva, and Kijun Han (2016)	Internet of Things-Based Energy Aware Smart Home Control System	Designed a ZigBee-based control system focused on energy efficiency and interference mitigation	Delivered energy control benefits, but lacked clarity in automation decisions, suggesting the need for XAI integration..

8	Vamsikrishna Patchava, Hari Babu Kandala and P Ravi Babu (2015)	A Smart Home Automation Technique with Raspberry Pi using IoT	Developed a Raspberry Pi system for appliance control and surveillance via computer vision	Enabled remote automation and video streaming, though lacked explanation mechanisms for user comprehension.
9	Majid Al-Kuwari, Abdulrhman Ramadan, Yousef Ismael, Laith Al-Sughair and Adel Gastli (2018)	Smart-Home Automation using IoT-Based Sensing and Monitoring Platform	Implemented NodeMCU with EmonCMS to monitor comfort-related variables and control appliances	Successfully tracked indoor conditions, but did not include features to explain system-triggered responses.
10	Leandro Filipe, Ricardo Silva Peres and Rui Manuel Tavares (2020)	Voice-Activated Smart Home Controller Using Machine Learning	Voice recognition integrated with online machine learning and IoT-based device control	Developed a locally adaptive smart home controller that learns user preferences in real-time. Demonstrated improved personalization and autonomy without relying on cloud connectivity..

Table 1: Comparison table

4.Research Gaps

Based on the literature review, several research gaps have been identified For Interpretable Deep Neural Networks using SHAP and LIME for Decision Making in Smart Home Automation :

1. **Limited Focus on Deep Learning Models:** It heavily depends on conventional machine learning methods for activity recognition, and there is a gap in knowing how interpretability techniques such as SHAP and LIME work with deep learning models like LSTM, CNN, or Transformers. These models are better adapted to identifying temporal and spatial relationships in sensor data but tend to be used as black boxes. Investigating their interpretability is challenging and offers possibilities for enhancing accuracy and user trust in smart home systems.
2. **Integration into Automated Decision Loops:** Though the foundation paper is centered on producing explanations for activity recognition, it does not extend to fully incorporate those explanations into automated decision-making in the smart home. There is a missing link in creating systems that can leverage explanation output to influence or adjust live decisions. Integrating interpretability into control logic—e.g., initiating or stopping an automation on the basis of explanation confidence or user input—can add to the intelligence and robustness of smart home automation.

5.Proposed Method

The project "Interpretable Deep Neural Networks using SHAP and LIME for Decision Making in Smart Home Automation" uses the following method: A deep learning-based activity recognition system is created employing models such as LSTM or CNN to process smart home sensor data and automate decision making. For transparency, SHAP and LIME are used to explain the model's prediction by identifying significant sensor inputs contributing to each decision. These observations are then converted into user-friendly natural language explanations, fostering trust and comprehension. The system facilitates real-time decision-making and has a feedback loop to continuously enhance model accuracy and explanation clarity, and it is appropriate for intelligent and interpretable smart home automation.

6.Conclusion

In the project, it presents the successful coupling of SHAP and LIME with deep neural networks to enhance decision-making for smart home automation. Through the provision of explainable AI actions, like changing lighting or regulating temperature, the system builds user trust and knowledge of automated processes. This solution not only ensures smart home systems work in an ethical and responsible way but also ensures energy efficiency, security, and comfort. The integration of state-of-the-art deep learning methods with the help of explain tools promotes an accessible, accountable, and user-centered smart home ecosystem.

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