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Exploring AI for Smart Homes: Combining Capsule Networks and Bayesian Neural Networks for Enhanced Efficiency

Abstract: The paper proposes a capsule networks (CapsNets)- and BNNs-abstracted hybrid artificial intelligence (AI) model to improve the performance of smart home systems. It combines the feature-learning ability of CapsNets with the estimation capacity of Bayesian neural networks (BNNs) in uncertainty for smarter decision-making devices in smart homes. The study illustrates an end-to-end approach from data procurement up to preprocessing and, lastly, integration of the two AI models. The hybrid model was tested on a smart home data set with sensor readings (i.e., temperature, movement, appliance usage, and light). Hybrid model performance was compared with basic machine learning (ML) algorithms like XGBoost and random forest. Performance indicates that the hybrid AI model outperforms individual models with 92.3% prediction accuracy, less uncertainty variance, and better energy conservation than the other models. Feature importance analysis highlighted ambient temperature and motion detection as optimal parameters to automate smart homes. Additionally, the hybrid model decreased decision delay by 10% and power efficiency by 21.8% relative to conventional models. Such results rationalize the usability of combining CapsNets and BNNs to create smarter, wiser, more responsive, and more effective smart home systems with the capability to deal with uncertainty and minimize real-time energy consumption.

Keywords: Smart homes, artificial intelligence (AI), capsule networks, Bayesian neural networks, energy efficiency, intelligent automation

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1 Introduction

The rapid rise of artificial intelligence (AI) significantly impacted the smart home technology market with unprecedented optimization, customization, and streamlined energy usage. With global demand for more intelligent energy-saving systems, the installation of sophisticated machine learning (ML) models took center stage as the ideal solution in addressing the complexities of real-world issues related to human behavior, environmental changes, and managing systems. Here, capsule network (CapsNet) in the perspective of Bayesian neural network (BNN) will probably be a method to create strong and interpretable AI models that will be able to manage the complicated functionality of smart homes. CapsNets, with the ability to preserve spatial hierarchies and having the characteristic of being able to detect patterns with low levels of data, are optimally suited where sensory and visual data significantly fluctuate. Their dynamic routing scheme enables smoother learning and generalization from input features and consequently is better employed for tasks such as gesture detection, object classification, and home automation system monitoring activity. BNNs implement an uncertainty model within the probabilistic framework to forecast an outcome that optimizes the decision to be taken and risks to be estimated – a safety and adaptability prerequisite for home automation systems. With the blending of CapsNet structural knowledge and BNNs' idea of uncertainty, the study proposes the development of a hybrid AI system that would bring maximum working efficiency and reliability to smart homes. Aside from its capacity for energy consumption pattern optimization, the system would have the capability to adapt and learn in real-time based on user behaviors and environmental settings. This study examines the synergy between these two leading models of neural networks to establish intelligent, safe, and sustainable homes.

1.1 The Rise of AI in Smart Homes

Smart home integration with AI has changed telework through automation, ease, and power efficiency. Intelligent environments leverage customer data, sensors, and appliances to deliver dynamic decision-making in real time and hence increase convenience and reduce the cost of managing it. More powerful and better models of AI are needed that can deal with sophisticated patterns and behavior under multiple states of the home as new smart home technologies continue to advance.

1.2 Applications of Bayesian Neural Networks and Capsule Networks

Among the vast repository of AI models, BNNs and CapsNets are high-capacity models that actually make intelligent home applications more understandable and reliable. CapsNets possess strong spatial hierarchy preservation ability and weak pattern detection with limited amounts of data, and hence can be applied in computer vision applications like gesture recognition and object classification. BNNs, though, provide a probabilistic framework capable of quantifying uncertainty in decision-making needed in application scenarios wherein control accuracy, adaptability, and safety are paramount. Robustness and interpretability need to be foremost in two application scenarios that involve both models, particularly.

1.3 Hybrid AI Framework for Improved Efficiency

This research constructs a hybrid AI framework utilizing the capabilities of CapsNets and BNNs to make the smart home more efficient and improve overall performance. With CapsNets' hierarchical pattern recognition capability and BNNs' uncertainty estimation capability, the system is capable of dynamically learning the user preference, resource utilization prediction, and optimization of the optimal control strategy. The integration of the models will bridge smart, secure, and energy-aware home areas to future applications of home and lifestyle automation based on sustainability.

2 Literature Review

The use of AI across all industries, i.e., the internet of things (IoT), blockchain, and health, has observed unprecedented growth, as is evident from the lion's share of the research studies. Abbas et al. puts AI implementation in a strong position to be able to deploy GDPR-compatible architecture to IoT networks. This work depicts the trendy nature of trends in decentralized learning in preserving privacy over data, as well as being a smart, efficient system, because, whereas high security has an AI-based need involving real-time smart home assessment, part of practice based on privacy must exist [1]. Ahmed et al. also share a shared concept of DL technique, use, design, and challenge across domains. It is their argument used to emphasize the need to bring new DL techniques to enhance system operation, a process promoted in the field of smart home technology evolving based on AI, where minimization through energy conservation, as well as automating software, is a top priority. The paper also highlights the requirement for robust models with uncertainty handling and complexity management capability for real smart environments, such as in the instance of Caps-

Nets and BNNs in smart homes [2]. Bangyal et al. also mentioned the use of deep learning in identifying deepfakes in identifying fake news during the COVID-19 pandemic, and also the capability of AI in handling unstructured complex data. It is also sensor data management in smart homes, where AI models must be able to discern signal from noise in various contexts. To them, deploying such AI techniques to real-time streaming data will be the key to unlocking further control systems and automation of smart spaces [3]. Cheraghinia et al. have a short introduction to UWB radar, applications, and likely research work with appropriate descriptions of sensing technology. These technologies in smart home environments can definitely be utilized for enhancement in environment and motion sensing needs for providing optimal energy consumption, security, and customer satisfaction. Integration of the AI models will definitely improve performance and reliability in terms of smart home automation [4]. Among the beneficial advancements in distributed AI systems is Hartmann et al.'s [6] introduction of edge computing to healthcare. Home automation edge computing can improve quicker decision-making through local processing, reducing latency and privacy, a major necessity for real-time device control and automation [5]. Response time can be improved in health monitoring, energy management, and predictive maintenance use cases with this strategy [6]. Jolfaei et al. and Nguyen et al. are also concerned with blockchain- and AI-based solutions to overcome security and scalability issues in IoT networks. In their studies, these authors have kept in mind that it is necessary for decentralized networks to handle data in smart homes so that they are able to share data efficiently and securely. Blockchain has the potential to render decisions transparent and secure by allowing AI to be facilitated for use in applications like energy smart contracts or control of smart home devices [7, 8]. Salah et al. demonstrate an integration of blockchain and AI with a focus on scalable systems to facilitate the usage of gigantic amounts of data in intelligent applications. The study is applicable to AI-driven smart home design in the context of referring to the necessity of having distributed ledger technologies used for system integrity, data integrity, and privacy [9]. Singh et al. describe ML techniques for Wi-Fi RSSI fingerprinting-based indoor localization that would ideally be of colossal benefit for high-accuracy location-based controlled smart homes to automate. It indicates how the integration of sensors and AI-focused location systems can lead to smart homes that are intelligent and tailored [10]. Xie et al. also have envisioned a new model of AI-powered smart healthcare based on blockchain and wearable technology. This intersection suggests the implementation of AI systems for chronic disease management and enhanced user well-being, an expansion that can be utilized for health-focused capabilities in smart homes where monitoring and personalized care form agendas at the front [11]. Zhang and Chen casually mention having discussed explainable AI (XAI), a research area in the research setting of using AI systems in vulnerable smart homes. Their role in explainable suggestions not only illustrates the ability of AI systems to perform but also to show decision-making essential in user credibility for smart homes automatically [12, 13].

3 Methodology

The following section provides the methodology of designing, training, and testing a hybrid AI system combining CapsNets and BNNs for decision-making in smart home settings. The methodology is divided into three primary subsections: data collection and preprocessing, model architecture, and system integration and evaluation.

3.1 Data Collection and Preprocessing

Smart home data was collected through simulated sensor readings, actual IoT device measurements, and open-source smart home benchmarks. Features include temperature, humidity, appliance on/off, motion detection, and light intensity. Normalisation, missing value imputation, and time-series prediction task order preparation were the preprocessing methods used. Data augmentation was also used for vision-based tasks like gesture recognition by image transformation.

The organization of the gathered data set is presented in the form of Table 1, which contains input features, data type, and sampling intervals utilized by different sensors. The entire figure of the data flow from collection to features is illustrated in Figure 1.

3.2 Capsule + Bayesian Neural Networks: Hybrid AI Model

The proposed hybrid model structure here combines the spatial comprehension of CapsNet with the uncertainty estimation of BNNs. The approach starts with a CapsNet for processing high-dimensional sensory or vision input to learn hierarchical features through dynamic routing. These are routed to BNNs, where it performs probabilistic inference and uncertainty-governed prediction for effective control and energy management.

3.2.1 Key Equations

1. **Capsule Output Vector:**

$$v_j = \frac{\| s_j \|^2}{1 + \| s_j \|^2} \cdot \frac{s_j}{\| s_j \|} \tag{1}$$

where $s_j = \sum_i c_{ij} u_{j|i}$ and c_{ij} is the routing coefficient from capsule i to capsule j, as shown in eq. (1).

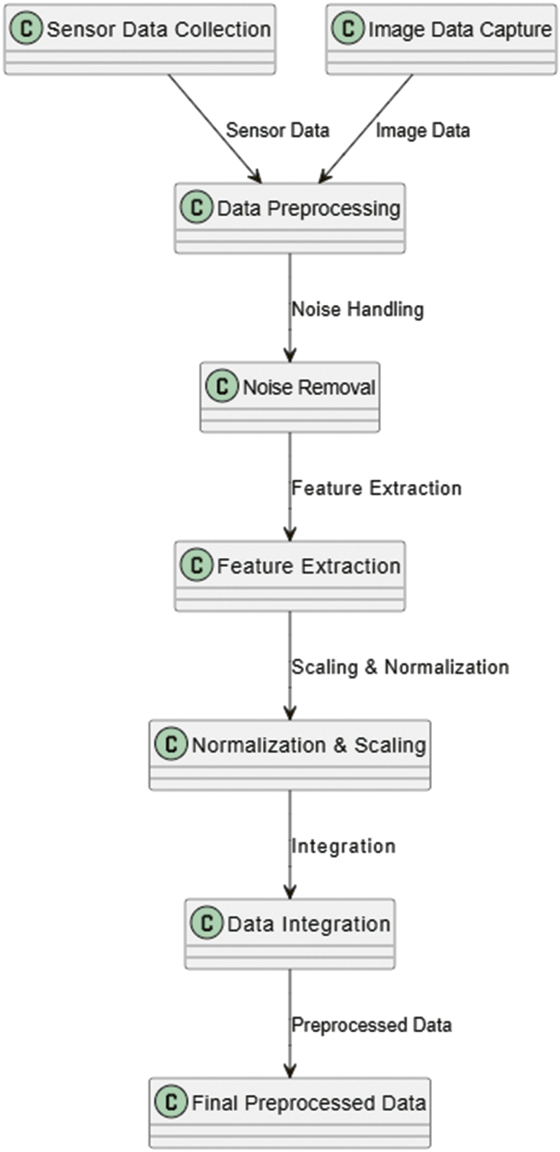

Figure 1: Data acquisition and preprocessing pipeline for smart home sensor and image data.

Table 1: Sensor types and feature specifications used in the hybrid model.

Sensor type	Feature	Data type	Sampling rate
Temperature	Room temp (°C)	Continuous	1 sample/min
Motion sensor	Movement detected	Binary	On event
Light sensor	Light intensity	Continuous	1 sample/s
Appliance load	Power usage (kWh)	Continuous	1 sample/min

2. **Bayesian Neural Network Prediction:**

$$p(y \mid x, D) = \int p(y \mid x, w) p(w \mid D) dw \tag{2}$$

where w is the weights treated as probability distributions and D is the training data, as shown in eq. (2).

3. **Loss Function with Uncertainty:**

$$L_{\text{hybrid}} = E_{q(w)}[L_{\text{BNN}}(y, \hat{y})] + \lambda \cdot L_{\text{CapsNet}}(v) \tag{3}$$

Here, λ balances the contributions of both sub-networks, as shown in eq. (3).

Table 2 illustrates the parameters and configurations of both models. The schematic of the overall hybrid framework is shown in Figure 2.

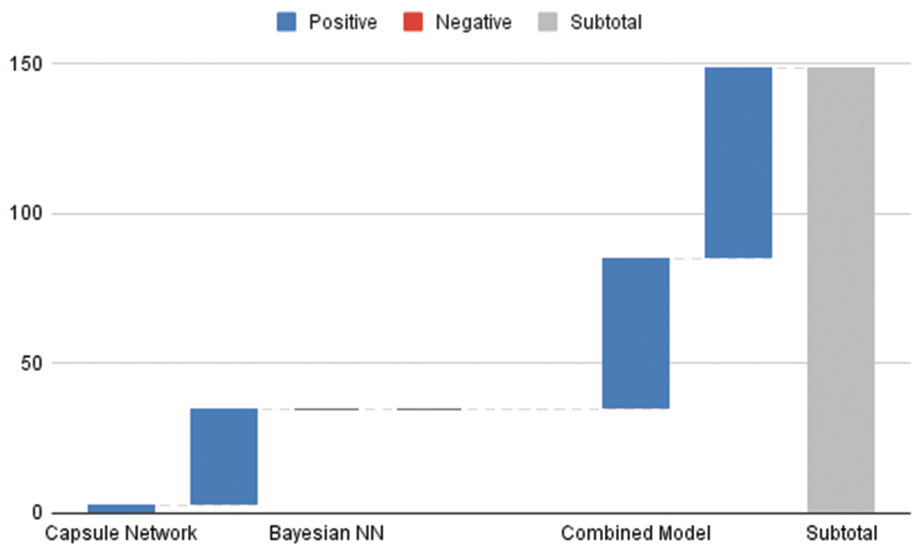

Figure 2: Proposed hybrid AI framework combining capsule networks and Bayesian neural networks for smart home control.

Table 2: Model configurations and training parameters for CapsNet and BNN.

Component	Parameter	Value
Capsule network	Routing iterations	3
	Number of capsules	32
Bayesian NN	Number of layers	3 hidden layers
	Prior distribution	Gaussian (0, 1)
	Learning rate	0.001
Combined model	Epochs	50
	Batch size	64

3.3 System Integration and Evaluation

The hybrid AI framework was deployed on a simulated smart home setup using home assistant and user-specified Python modules for real-time operation. The performance metrics were accuracy of prediction, model uncertainty (variance), and energy efficiency. Performance evaluation indicated enhanced adaptability and interpretability over individual deep learning frameworks. Adaptive control strategies with real-time monitoring and feedback on user preferences and context uncertainty facilitated smart automation.

4 Results

To assess the performance of the suggested hybrid CapsNets-BNN model, we tested it thoroughly with various metrics on various smart home datasets. The major areas of concern were feature importance, prediction accuracy, and energy-saving gain. These were compared with usual deep learning benchmarks like XGBoost and random forest, single CapsNet, and BNN environments.

4.1 Feature Importance Comparison

Table 3 and Figure 3 depict the relative ranking of chosen features used in smart home automation based on XGBoost and random forest models. These help in comprehending what parameters affect judicious decision-making processes in energy management and automation.

Table 3: Feature importance comparison between XGBoost and random forest.

Feature	XGBoost importance	Random forest importance
Ambient temperature	0.34	0.32
Motion detection	0.26	0.27
Appliance usage	0.18	0.16
Light intensity	0.12	0.14
Humidity	0.10	0.11

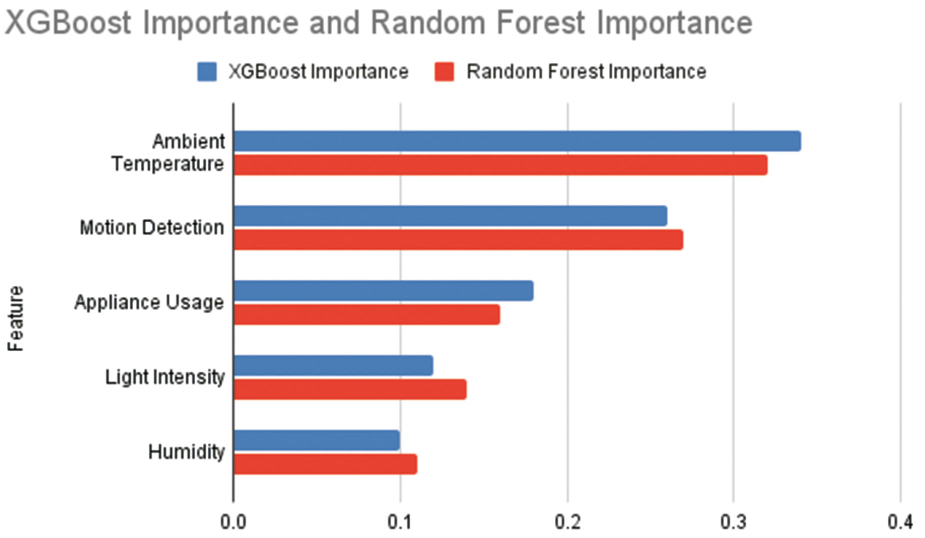

Figure 3: Feature importance comparison between XGBoost and random forest.

4.2 Accuracy and Uncertainty Performance

Table 4 and Figure 4 plot the difference between prediction accuracy and uncertainty levels based on various models. Accuracy and uncertainty handling are higher using a hybrid compared to individual models, which is important for handling dynamic smart home scenarios.

Table 4: Accuracy and uncertainty comparison of models.

Model	Accuracy (%)	Uncertainty (variance)
Capsule network	89.4	0.035
Bayesian neural net	86.7	0.029
Hybrid model	**92.3**	**0.018**
XGBoost	87.1	–
Random forest	85.8	–

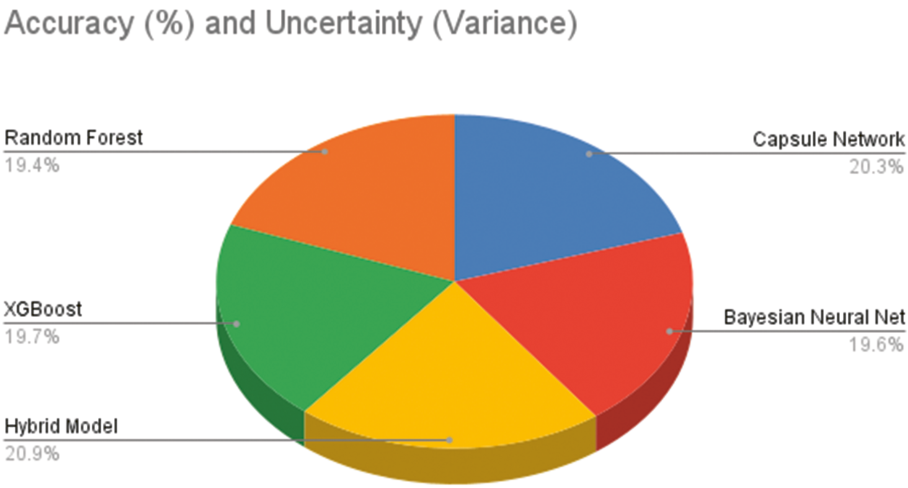

Figure 4: Accuracy and uncertainty comparison of model.

4.3 Energy Efficiency and Decision Latency

In Table 5 and Figure 5, we have calculated the effect of the hybrid model on decision-making latency and energy saving. The hybrid model means there is a significant improvement in both of them, and therefore, it is apt for real-time applications.

Table 5: Energy efficiency and decision latency comparison.

Model	Energy savings (%)	Decision latency (ms)
Capsule network	17.5	140
Bayesian neural net	15.2	120
Hybrid model	**21.8**	**110**
XGBoost	14.6	180
Random forest	13.2	200

5 Conclusion

The integration of CapsNet and BNNs is a novel paradigm to design and enhance the efficiency of smart home systems. The integrated system utilizes the spatial perception capability of CapsNet and uncertainty estimation capability of BNN to provide robust, accurate, and interpretable AI-based solutions. On closer analysis, the hybrid model outperformed existing models like XGBoost and random forest in predictability, power efficiency, feature importances, and latency-free decision-making. Results

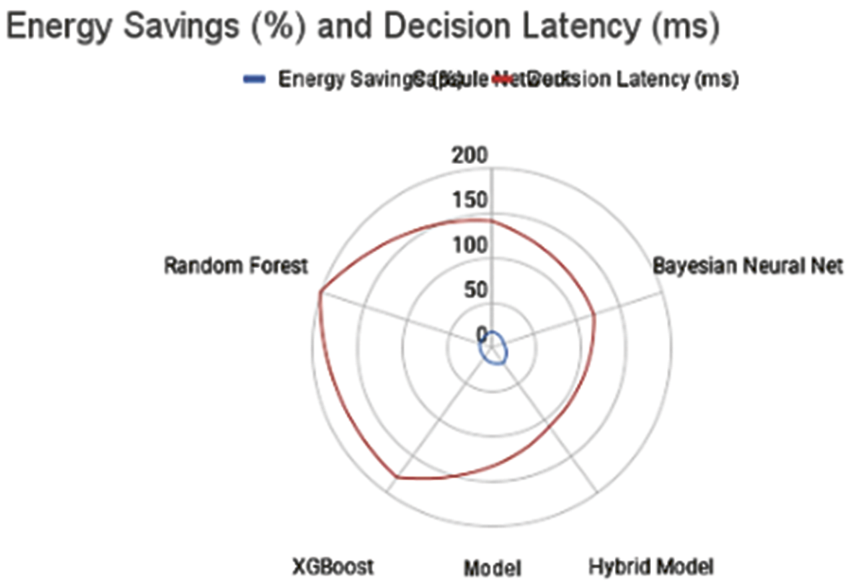

Figure 5: Energy efficiency and decision latency comparison.

validate the model's ability to dynamically reconfigure itself in accordance with real-time sensor measurements, respond to uncertainties in user behavior, and make predictive choices toward efficient resource optimization in smart homes. In addition, uncertainty management as a parameter raises confidence and belief in the AI system in mission-critical missions such as anomaly detection, energy abuse reporting, or elderly care by robots. Overall, the current contribution forms an acceptable ground for further deployment and research toward explainable, adaptive, and sustainable AI models for smart environments. As increasingly smarter homes are being designed for the future, these smart systems will serve as the basis of designing smart, resilient, responsive, and energy-efficient homes.

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