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Energy Management for Internet of Things-Based Smart Buildings Using a Novel Deep Learning Technique

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Abstract: On a global scale, the main challenges encountered by many sectors, including industrial and residential sectors, are to energy use and conservation. This study introduces an innovative approach that integrates deep learning and Internet of Things (IoT) technologies to efficiently control the operation of electrical systems, with the objective of reducing energy consumption. To achieve a somewhat ambitious goal, we have developed a people recognition system that utilises deep learning techniques and employs the YOLOv3 algorithm to precisely ascertain the number of individuals inside a certain area. Hence, the effective administration of electrical equipment operations may be attained inside a smart building. Furthermore, the number of persons and the operational status of the electrical equipment units are made publicly available through the internet and presented on the dashboard of the Internet of Things (IoT) platform. The technology being evaluated enhances the decision-making process for energy utilisation. To assess the effectiveness and practicality of the suggested approach, a set of comprehensive test scenarios is carried out inside a specifically designed smart building setting, with consideration given to the existence of electrical equipment units. The findings from the simulation demonstrate the efficacy of the recognition algorithm based on deep learning in accurately identifying the quantity of humans present in a certain area.

Keywords: *Internet of Things (IoT), deep learning, power consumption, Industry 4.0.*

1. Introduction

The significant influence of Artificial Intelligence (AI) in solving decision-making challenges within the framework of the big data dilemma has been widely acknowledged. Individuals are beginning to contemplate if their future engagement and assimilation with artificial intelligence (AI) leans more towards supplanting rather than enhancing human decision makers. Nevertheless, despite the rapid advancements in artificial intelligence, computational systems, autonomous technologies, and intelligent decision-making tools, it is important to note that decision-making processes will continue to prioritise human involvement. This holds true even in the transition from Industry 4.0 to Industry 5.0. As stated by reference [1], Industry 5.0 is projected to usher in a transformative era known as the "Age of Augmentation," characterised by a profound symbiotic relationship between humans and machines.

The majority of processes in contemporary industry, such as smart manufacturing, Industry 4.0 and 5.0, are propelled by decision-making. This decision-making involves the intelligent allocation of decision power among various entities, including individuals, AI and Machine Learning (ML) models, autonomous agents, robots, and other intelligent components. Nevertheless, it is essential to maintain the fundamental role of humans in the decision-making process. In their work, Bruzonne et al. [2] proposed dynamic planning as a field of study that examines the interaction between Industry 4.0 and other decision-making paradigms. This discipline emphasises the pivotal role of artificial intelligence, alongside modelling, simulation, and data analytics, in achieving synergy across these domains.

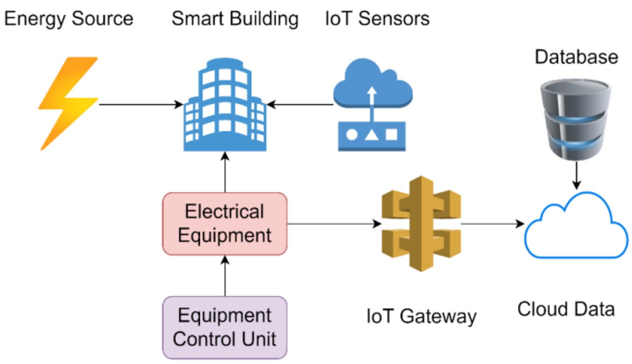

Fig. 1. General structure of IoT based Smart building structure

The implementation of Industry 4.0 necessitates the development of well-designed artificial intelligence (AI) models that can effectively assist humans in addressing a wide range of decision-making challenges. These

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challenges span from routine manufacturing decisions to more strategic ones, as well as from typical business decisions to those arising in critical emergency situations [3]. Furthermore, the scope of decision models extends from individual decision-making to collaborative and adaptable decision facilities that can effectively manage crises, such as the COVID-19 pandemic.

Longo et al. [4] argue that within the context of Industry 4.0, human elements continue to have significant importance, even in highly computerised procedures like intelligent defect detection and alert management. The issue of predictive maintenance, which is both popular and significant, need human participation since its real-world applications are still few [5]. This scarcity may be attributed to the inadequate availability of high-quality surveillance information as well as the subpar customer satisfaction associated with the use of AI methodologies and tools.

Hence, the human factor continues to hold significance in the context of industrial decision-making, serving as an integral part of a diverse decision-making group and as a recipient of the resulting decisions. Nevertheless, it is important for individuals to possess a comprehensive understanding of both the choice itself and the underlying process and rationale in order to effectively participate in decision-making and successfully implement the chosen course of action. As seen in previous research [6], individuals utilising real-time process forecasts in smart factories must develop a sense of trust in the predictions and proposed judgements that are generated automatically. The field of Explainable AI (XAI) has arisen with the purpose of facilitating human comprehension, trust, and control over the artificial intelligence systems they interact with. Hence, there exists a significant need for explicit declarative knowledge associated with extensive ontologies in order to facilitate transparency, accountability, and trust within industrial applications of artificial intelligence and machine learning.

However, as seen in previous research [7], the primary challenges in achieving explainability are associated with the use of deep learning models in the context of cyber-physical systems. These models rely on artificial neural networks, which lack the ability to directly observe the relationship between input and output. Contrasting to deep artificial neural networks, decision trees are recognised as a form of interpretable models generated by machine learning procedures. Decision trees are a method of data analysis that effectively combines straightforward inquiries about the data in a comprehensible manner. Consequently, their formal depiction facilitates the automated derivation of explicit decision rules.

In addition to the well-known C4.5 algorithm commonly employed for learning decision trees from data, John Ross Quinlan proposed an alternative method (Quinlan, 1994) for converting these trees into concise sets of production rules. This approach is particularly suitable for communicating information in technological examinations and preservation infrastructure, as it provides a transparent and practical formalism. Nevertheless, the methodology employed by the researcher necessitates the utilisation of a training dataset consisting of examples that have been used to construct the decision tree. Performing a direct transition from a decision tree to a collection of rules is a job that is both tough and feasible [8].

Nevertheless, it is crucial to ensure the smooth and gradual integration of rules derived from distinct decision trees that have been trained independently, with other rules that were already in existence. The process of integration necessitates the exchange of shared ontologies across sets of rules and the representation of these rules in a standardised format, such as the Semantic Web Rule Language (SWRL). The SWRL was developed as a means of facilitating the sharing of rules due to the limited interoperability observed in previous rule-based systems [9]. The incremental updating capability of SWRL rules is facilitated by the support of the SWRL language for the Open World Assumption and monotonic reasoning.

Additionally, SWRL has gained recognition and endorsement from industry professionals. One study [10] presents a built domain ontology that is used to describe information related to predictive maintenance. Additionally, a set of SWRL prediction rules are employed to facilitate reasoning about the timing and criticality of equipment breakdowns. The study described in reference [11] focuses on the direct extraction of SWRL rules from a decision tree generated by the WEKA machine learning-as-a-service platform. This approach is applied to address the challenge of order allocation management in a manufacturing network of 250 small firms.

The significance of incorporating semantic technologies in the context of Industry 4.0 has been discussed in a previous study [12], particularly in relation to the automation of manufacturing processes and the implementation of intelligent condition monitoring systems. In addition, the author [13] asserts that the integration of machine learning models with semantic web technologies, specifically ontologies and reasoning, holds significance in addressing predictive maintenance issues. The integration of models is necessary for both condition monitoring and predictive maintenance problems. This integration is required since these models are often trained independently using data from various objects within the same asset class, such as electric motors of the same or comparable kind [14].

Another significant domain within the context of Industry 4.0 pertains to robots and autonomous systems, specifically agents, where the demand for explainable and easily interactable models is crucial. This domain necessitates interoperable simulations that prioritise predictive maintenance and security, particularly for independent crucial outreach [15]. The authors of [16] present a strategy for integration and interoperability that is applicable across several domains. This approach involves the use of autonomous agents as intermediaries to facilitate semantic reasoning across smart industrial assets that include embedded intelligence [17]. A comprehensive overview of the progress and achievements in semantic web research and applications over the past two decades can be found in reference [18].

Additionally, readers are encouraged to explore the interdisciplinary evaluations of the advantages of semantic technologies for cyber-physical systems in general [19], as well as for cyber-physical production systems specifically [20]. The evaluations consistently highlight the significant need for semantic innovations in the context of data and knowledge representation as well as reasoning within contemporary industries. This demand stems from the notable advantages offered by these technologies, particularly their exceptional degree of explainability and capacity for integration.

Another alternative for the integration and collaborative use of several machine learning models, which have been trained on separate decentralised datasets owing to ownership or privacy concerns [21], is known as federated learning [22]. When the individual models comprising a federated learning system lack explainability, the problem of explaining the decisions made by the federated learning process becomes intricate and presents an additional barrier for explainable artificial intelligence (XAI) [23].

Hence, a significant obstacle in the journey towards Explainable Artificial Intelligence (XAI) lies in the conversion of machine learning models, whether they are operating alone or in collaboration, from connectionist representations (such as deep neural networks) to symbolic representations (such as decision trees). Although there are various approaches available for converting decision trees into neural networks [24], as well as effective combinations of decision trees as well as artificial neural networks, the challenge of enhancing the interpretability of neural networks by transforming them into decision trees remains unresolved. Symbolic models, which are grounded in formal logic and employ deductive reasoning, exhibit important distinctions when compared to models that rely on neural networks.

The main contributions of the research article are as follows:

- The utilisation of deep learning in conjunction with Internet of Things (IoT) topology for the purpose of managing energy in smart buildings is proposed as a promising approach within the context of Industry 4.0. This paper presents a novel framework for the management of electrical equipment operations utilising the Internet of Things (IoT).
- Proposing the use of YOLOv3, a sophisticated intelligence algorithm, for the purpose of human identification. The automation of electrical equipment operation is achieved by utilising the number of individuals identified inside a designated region, as opposed to traditional techniques.
- The practise of displaying all events on the dashboard of the Internet of Things (IoT) platform. The functioning state of the electrical equipment is recorded on the IoT database in order to facilitate future analysis and effectively control energy usage.
- The approach under consideration exhibits potential for application across many devices, hence facilitating a reduction in both energy loss and associated costs.

2. Related work

In contemporary times, there is a notable surge in urbanisation, mainly observed in industrialised nations, resulting in a substantial escalation in the need for energy consumption. One of the contributing factors to the current challenges of contamination and global warming may be attributed to this particular cause. Electricity is generated by a variety of sources, including hydropower, nuclear fission processes, natural gas, coal, wind, and sunshine. These sources are considered to be finite energy resources.

Nevertheless, the over utilisation of resources is prevalent due to user behaviours like as Internet of Things (IoT) is an emerging technological paradigm that forms the foundation of the fourth industrial revolution, sometimes referred to as Industry 4.0. The Internet of Things (IoT) system encompasses many new technologies that provide wireless connectivity between physical items, commonly referred to as "things" within this system. The data-gathering sensors are integrated into Internet of Things (IoT) devices, including appliances, personal gadgets, and industrial equipment, enabling communication and control functionalities.

The advancement of IoT topology has enabled the use of online data acquired from sensors to enhance industrial operations and increase quality of life. Hence, this technology is widely acknowledged as a very notable advancement in future technology and has garnered significant attention for its potential to drive the fourth industrial revolution. A variety of Internet of Things (IoT) technologies have been created to facilitate the monitoring of energy use and enable energy conservation efforts. The use of the internet of things (IoT) has promise in addressing the need for intelligent energy management systems in buildings, with a particular focus on applications within smart cities.

According to reports, around 50% of the total energy consumption in buildings may be attributed to the domestic sector. This includes various activities such as cooking, lighting, heating, fans, and air conditioning (HVAC). Therefore, HVAC control systems play a significant role in the endeavour to decrease power usage. A suggested smart house architecture based on the Internet of Things (IoT) was designed with the aim of optimising energy consumption using intelligent mechanisms. In this particular instance, the lighting and heating/cooling system might be managed by the use of light and HVAC control systems, in conjunction with a security camera that incorporates motion detection. This would enable the remote activation or deactivation of these systems when a resident arrives or departs the residence.

Significant reductions in building energy use can be achieved by accurately detecting occupancy. This strategy has a significant potential for achieving energy conservation. A cost-effective sensor platform was developed and deployed for the purpose of detecting occupancy in individual office spaces. The optimisation of energy consumption in buildings may be enhanced by precisely estimating the occupancy count. However, this necessitates the implementation of a robust system capable of effectively detecting and providing information on the occupancy status. The passive infrared (PIR) sensor is commonly utilised for the purpose of detecting human movement and presence by measuring the infrared light emitted by objects. However, the analogue output waves of PIR sensors reflect the displacement of the body, its speed, and movement direction.

Consequently, the PIR sensors exhibit limitations in precisely discerning the quantity of individuals present inside a given area, especially when confronted with immobile human beings. Therefore, it is crucial to integrate more sophisticated machine learning methodologies in order to effectively gather, handle, and evaluate data in real-time due to the limited capabilities of Internet of Things (IoT) sensors utilised in smart buildings. The emergence of machine learning has led to the recognition of deep learning as a powerful tool capable of achieving end-to-end learning patterns and capturing extremely non-linear correlations within data.

Deep learning methods possess more complex structures compared to shallow ones, enabling them to acquire intricate characteristics. The training algorithms employed in this study demonstrate a high level of reliability, as they possess the ability to acquire valuable target characteristics autonomously, eliminating the necessity for manual extraction and selection of significant features. Undoubtedly, the utilisation of deep learning has shown to be a highly effective approach in addressing the complex challenge of recognising stationary human subjects in a nonlinear context.

The utilisation of an Internet of Things (IoT) platform integrated with a machine learning-powered energy monitoring system is a very promising strategy for the monitoring of intelligent buildings. This technique aims to effectively diminish energy usage while ensuring the maintenance of optimal levels of comfort and safety. The YOLO-v3 method has been widely recognised as a highly effective approach for object recognition within the field of deep learning. The purpose of developing this model is to enhance the speed of recognition in both offline and real-time scenarios. Nevertheless, this technique does have certain limitations, such as the potential for items to seem overly near in the image or the difficulty in detecting minute objects.

The use of the Darknet deep learning library in demonstrating YOLO has the capability to address challenges related to recognition. Moreover, it attains a cutting-edge level of performance in the realm of real-time object identification. The YOLO network is capable of identifying targets in an image without relying on the region proposal network. This is achieved using direct regression, enabling YOLO to achieve quicker detection capabilities. In recent times, the utilisation of the advanced iteration known as YOLOv3 has resulted in improved levels of precision, accuracy, and speed. Furthermore, it has been specifically optimised for the purpose of detecting tiny targets.

Motivated by the advancements in Internet of Things (IoT) and machine learning, this study proposes a people detection system based on deep learning. The primary objective of this system is to accurately determine the number of individuals present in a conventional smart building. By doing so, it enables the optimal management of existing electrical equipment systems, hence facilitating energy conservation. A novel algorithm is built, employing the YOLOv3 framework, to enable remote control of equipment. This algorithm operates by leveraging information on the number of individuals present and the state of electrical equipment, which is obtained through the Internet of Things (IoT) platform. The Internet of Things (IoT), an emerging technology, makes it easy and advantageous to share data with additional devices across wireless networks. However, due of their continual development and technological advancements, IoT systems are more vulnerable to cyberattacks, which could result in strong assaults.[30] [31]. The suggested topology has the potential to improve the process of decision-making about energy usage by transmitting data on the number of individuals and the operational state of electrical equipment over the internet to the dashboard of the Internet of Things (IoT) platform.

3. Proposed System Design

This section provides a comprehensive description of the architecture based on the Internet of Things (IoT), as it serves as the primary component of the suggested method. The use of intelligent energy management systems may effectively reduce energy consumption in buildings, while also enhancing the overall comfort and security of the premises. The structural electricity surveillance system described in this study adheres to the overarching architecture of the Internet of Things (IoT), encompassing devices, connectivity, cloud infrastructure, data collecting, and application modules. The system incorporates several Internet of Things (IoT) devices that are outfitted with electronic components, including sensors and microcontrollers.

These devices have the capability to seamlessly integrate and execute a wide range of tasks. In the context of environmental sensing, sensors are employed to detect and perceive the surrounding conditions. Subsequently, the acquired data is transmitted to cloud-based platforms via gateways to provide additional computational analysis and processing. The data is analysed in real-time, providing the user with full autonomy in the decision-making process. After the choice has been made, the necessary feedback is sent to the microcontroller on the system in order to activate or deactivate the units as required. This platform enables real-time monitoring of devices by the system.

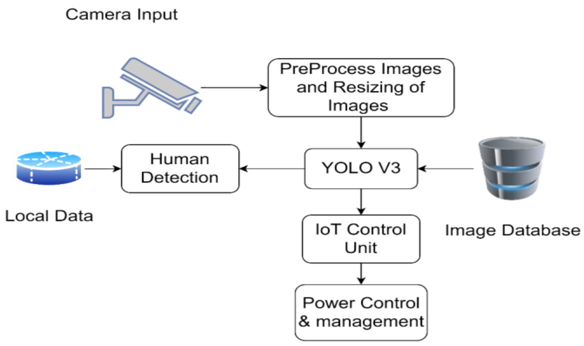

Fig. 2. Process Flow of proposed System

The process of data collecting can be facilitated by utilising many interfaces, including open platform interaction, Modbus, including the communication queued instrumentation transit network protocol. The implementation of data collection from devices can be achieved using different Internet of Things (IoT) platforms through the utilisation of edge computing and IoT cloud gateways. However, the monitoring of real-time processes is influenced by the selection of appropriate data acquisition methods, which includes considering relevant features, scaling and analysing the data, replication the power source data, and reducing the dimensionality of the data.

The selection of an acceptable approach is contingent upon the characteristics of the process phenomena in question. The programme involves the utilisation of the Touch Components for IoT, which is a comprehensive platform that encompasses edge connectivity and business applications. This platform enables clients to access and assess the acquired data efficiently through the use of a Digital Twin. Additionally, it facilitates intelligent monitoring of the devices. The CONTACT Elements for IoT use widely accepted MQTT protocols to provide the visualisation of data on a graphical dashboard. This data is subjected to diverse signal processing and machine learning algorithms before to its presentation. YOLO, short for "You Only Look Once," is a well-recognised convolutional neural network (CNN) that has gained prominence as an efficient technique for real-time object detection in the domain of deep learning.

The initial establishment of this concept was documented by J. Redmon et al. in their publication. The YOLO technique employs a distinct neural network architecture that processes whole pictures in a single computation, enabling the extraction of bounding boxes and confidences for different categories. The YOLO network is capable of doing regression analysis, enabling it to identify targets inside an image without relying on the regional proposal network. This enables YOLO to achieve high-speed detection. During both the training and testing phases, it has the ability to accurately identify and encode contextual information for all classes. Furthermore, the YOLO algorithm demonstrates an ability to identify and classify the inherent characteristics of various objects in a manner that can be applied to a wide range of scenarios.

Algorithm: Controlled Power consumption in Electrical equipment with YOLOv3

Input: Captured Images from the camera unit

Steps:

1. Execute resize module for image preprcessing step.

2. Give preprocessed images as input for YOLOv3 network.

3. Perform the recognition procedure utilising the YOLOv3 algorithm.

4. The quantity of individuals identified through the use of the MQTT interface is to be made publicly available.

5. Perform statistical analysis on IoT using contact components.

6. If the human beings identified in the image is one or exceeding one,

a. Transmit the binary signal "1" via the MQTT system to the microcontroller of the electrical equipment.

b. Establish the electrical connection for the power supply of the gadget.

c. Provide the numerical representation of individuals currently displayed on the

Internet of Things (IoT) dashboard.

d. Documenting the operational state of electrical equipment.

7. If no one is found in the image,

a. Transmit a signal denoted as "0" to the microcontroller of the electrical equipment

via the MQTT system.

b. Deactivate the power supply of the electrical device.

c. Provide the numerical representation of individuals displayed on the Internet of

Things (IoT) dashboard.

d. Document the occurrence of the deactivation of electrical equipment.

8. document all occurrences and relevant information within the system's database to facilitate additional investigation.

Hence, this approach has the potential to be seamlessly included into cutting-edge computer vision methodologies such as region-based CNN (R-CNN) and single-shot detection (SSD). The YOLO algorithm begins the visual process by partitioning the input picture into a grid of dimensions $(T \times T)$. Subsequently, the projected entity is centralised within the neural cell. Every individual cell within the neural network predicts a set of M bounding boxes and computes their corresponding confidence scores.

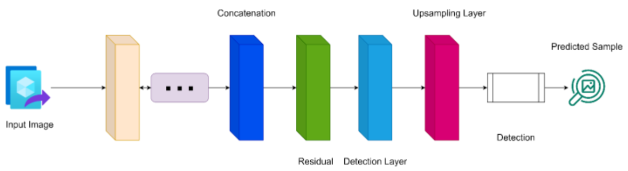

Fig. 3. General YOLOv3 structure

The confidence score is determined by two factors: the likelihood of the estimated box accurately capturing an item $(Q(p))$, and the performance of the predicted box in terms of intersection over union $(\cup_p^t I)$ with the ground truth. Therefore, confidence scores are defined as the product of the probability $(P(p))$ and the Intersection over Union between the ground truth and the predicted object as the confidence value such that $c = P(p) * \cup_p^t I$.

$$P(p) = \begin{cases} 1 & \text{the score value matches } \cup_p^t I \\ 0 & \text{Otherwise} \end{cases} \quad (1)$$

The detection of the centre of objects within each grid cell may be achieved by making predictions on a set of class probabilities, denoted as $D = P(p)(C_j|O)$. This approach remains effective regardless of the variable number of M boxes. The assumption is made that the contribution from a grid cell is contingent upon the presence of an object within it.

Each anticipated box comprises five elements (p, q, r, s, c), where (p, q) denotes the centroid of the box relative to the relevant grid cell. The variables r and s represent the weight and height, respectively, of the full picture. The process of normalising the four coordinates (p, q, r, s) involves rescaling them to the range [0, 1]. During the testing phase, the class-specific confidence score for each box is calculated by multiplying the individual box confidence estimation with the class-conditional probability as follows:

$$P(p)(C_j|O) \times P(O) \times \cup_p^t I = P(C_j) \times \cup_p^t I \quad (2)$$

The proposed approach considers both the fitness of the estimated box with respect to the goal and the observed likelihood of class-specific targets within the box. Throughout the training phase of the YOLO algorithm, the loss function is defined according to Equation (3). In this equation, C_j denotes the confidence scores, O_{ij} indicates the presence of objects, and the prediction is given by the j^{th} enclosing box prediction.

$$M_{loss} = \theta_c \sum_{i=0}^{t^2} \sum_{j=0}^{M} O_{ij}[(x_i - \hat{x}_i)^2 - (y_i - \hat{y}_i)^2] + \theta_c \sum_{i=0}^{t^2} \sum_{j=0}^{M} O_{ij} \left[\left(\sqrt{r_i} - \sqrt{r_i}\right)^2 - \left(\sqrt{s_i} - \sqrt{s_i}\right)^2\right] + \theta_n \sum_{i=0}^{t^2} \sum_{j=0}^{M} O_{ij}[(P_i - P_i)^2] \quad (3)$$

The regulation of training stability is determined by two factors, namely θ_c and θ_n. The YOLO network initially consists of 24 convolution layers that are responsible for feature mapping. Subsequently, two fully connected layers are employed to ascertain the geographic location of the bounding box and the corresponding probabilities of the objects. The measurement of depth of the feature maps is reduced by the use of alternating 1 × 1 convolutional layer. The network has the capability to do picture processing at a rate of 45 frames per second. However, a faster variant of YOLO can achieve a processing speed of 155 frames per second, but with a trade-off in terms of reduced accuracy. A more advanced iteration of YOLOv2 has been created with the aim of achieving quicker performance compared to alternative recognition methodologies. The system has the capability to process images of different sizes in order to optimise the balance between speed and accuracy.

The introduction of YOLOv3, the third iteration of the YOLO algorithm, has resulted in improved speed and accuracy compared to its predecessors, YOLOv1 and YOLOv2. The YOLOv3 network has the capability to enhance its performance across various sizes through the incorporation of larger dimensions and the inclusion of shortcut links to residual networks. Hence, it possesses the capability to execute intricate object identification tasks with exceptional accuracy, even for objects of diminutive size. This paper presents an overview of the proposed YOLOv3 method, which involves the input of camera images into the network to estimate the output of bounding boxes, followed by the detection of individuals.

The feature extraction network is enhanced by replacing the fully linked layer and pooling layer with a residual network. This enables the network to sustain convergence in the context of deeper learning and enhance training performance. Additionally, the feature extraction process is derived from the Darknet-53 network, which enables the acquisition of more comprehensive and profound feature information. The network forecasting process starts by feeding input pictures of dimensions 420 × 420 into the Darknet-53 network, which consists of an aggregate of 52 convolutional layers.

This architecture has been designed to enhance overall performance. Subsequently, a series of convolutions are performed, followed by five down samplings. The feature map at the lowest level of down-sampling measures 13 × 13, whereas the two feature maps at higher levels of up-sampling measure 26 × 26 and 52 × 52, correspondingly. The proposed YOLOv3 network has a downsampling factor of 32 for the input recognition picture and includes a route layer specifically designed for shallow feature identification.

The DarkNet architecture incorporates a double up-sampling process in both the middle layer and the fifth layer, followed by the stitching of the up-sampled outputs onto the feature map. The YOLOv3 algorithm generates three feature maps as its output. The evaluation of feature maps of different sizes is conducted to recognise tiny things. Hence, it possesses the capability to identify objects of considerable size inside an image. Within the network output, the predictions for bounding boxes in each cell of the feature map are performed. These predictions include the centre coordinates (D_x, D_y) and the size (D_a, D_b) of the bounding box. The estimation of bounding box coordinates (V_p, V_q, V_r, V_s) is conducted using the YOLOv3 algorithm. The variables P_x and P_y denote the displacement or deviation of the cell. The variables Q_a and Q_b represent the dimensions of the bounding box prior to making any predictions.

$$D_x = \theta(u_x) + P_x \qquad (4)$$

$$D_y = \theta(u_y) + P_y \qquad (5)$$

$$D_a = Q_a e^{u_x} \qquad (6)$$

$$D_b = Q_b e^{u_y} \qquad (7)$$

The following architectural diagrams discusses how the proposed approach has been utilized for conducting energy management operations with the system.

4. Results and Discussion

Within this subsection, the implementation of the deep learning architecture is conducted utilising the YOLOv3 method with the aim of detecting the quantity of individuals present within a designated region. This study uses the YOLOv3 algorithm, a deep learning-based approach, to recognise and count individuals inside a designated region. The purpose of this analysis is to effectively regulate the operation of electrical equipment with the aim of enhancing energy efficiency. The YOLOv3 model proposed in this study is trained using the WiderFace dataset, a widely recognised benchmark dataset for face identification.

The dataset is derived from the publicly accessible broader dataset, which has a total of 6000 images and includes 3500 tagged face images. The log data pertaining to every cycle of the model's training algorithm was gathered. In addition, the YOLOv3 model is evaluated using a sample photograph to verify its capacity to accurately detect a substantial quantity of individuals, prior to its deployment in real-time scenarios. Subsequently, the model may be employed to evaluate the efficacy of real-time face detection using the camera. A certain quantity of individuals is quantified and transmitted to the Internet of Things (IoT) broker utilising the Message Queuing Telemetry Transport (MQTT) protocol.

Additionally, the microcontroller is responsible for detecting the state of electrical equipment. Subsequently, the current condition of the electrical equipment is transmitted to the IoT broker via the MQTT protocol. The gateway performs facial recognition on individuals and afterwards transmits the count of people to the IoT broker. The Internet of Things (IoT) platform employs a comparative analysis of the quantity of individuals present and the operational condition of electrical equipment in order to arrive at a determination. The circuit in question facilitates the automated functioning of electrical equipment by taking into account the quantity of individuals presents inside a designated space.

In addition, the circuit is implemented with a manual operation as a contingency measure instead of relying solely on automatic operation. This ensures the uninterrupted functioning of electrical equipment in the event of any issues encountered by the automatic circuit. The camera is responsible for detecting individuals within a designated area, while the gateway employs the YOLOv3 algorithm to ascertain the count of people. Subsequently, this count is transmitted to the IoT platform using the MQTT protocol. In the event that no one is present within the designated vicinity, the Internet of Things (IoT) platform will transmit a signal denoted as "0" to the microcontroller after a certain period of time, utilising the MQTT protocol. The purpose of this signal is to initiate the disconnection of power to the electrical equipment.

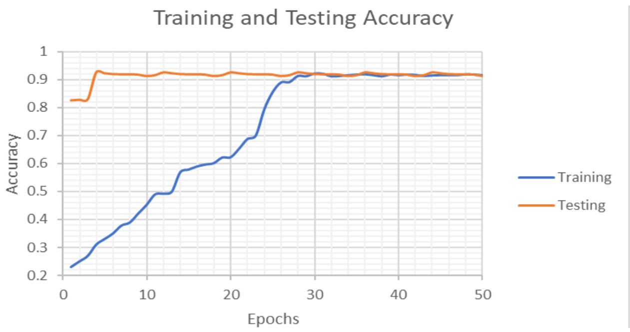

Fig. 4. Training vs Testing accuracy of Deep learning model

The electrical equipment is deactivated following a predetermined time delay, as it is possible that individuals within the designated area may have temporarily vacated the area to fulfil a duty, prior to their return to the vicinity of the electrical equipment. In the event that individuals are present within the designated space, the Internet of Things (IoT) platform will transmit a wireless signal, denoted as "1," to the Arduino device. This signal serves to establish a connection and enable the power supply of the electrical equipment. However, it is important to note that individuals are required to utilise the respective remote control of the electrical equipment in order to operate it, as the act of operating said equipment remains discretionary for individuals.

In order to provide comprehensive coverage of the designated area, the experimental procedure is conducted within a spatial extent of 3 × 6 square metres. The aforementioned problem serves as the primary constraint of our methodology. Before implementing the recommended energy management plan, it is imperative to carefully pick an appropriate camera. In addition, in the event of an interruption in the automatic control mechanism caused by internet disconnection, our Internet of Things (IoT) system is equipped with a contingency system that ensures the uninterrupted operation of the electrical equipment. The ultimate outcome of tallying the quantity of individuals and the functioning of electrical equipment will be documented in the database server and shown on the dashboard of the Internet of Things (IoT) platform. The YOLOv3 algorithm, as suggested, is designed to identify and quantify the presence of individuals inside a designated region. It accomplishes this by utilising the MQTT protocol to transmit the count of detected humans to the IoT platform.

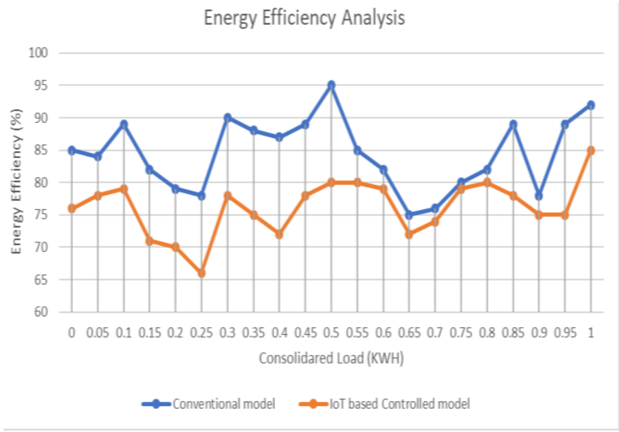

Fig. 5. Energy Efficiency Analysis

The Internet of Things (IoT) platform does an analysis of the signal pertaining to the quantity of individuals present. In the event that the quantity of individuals exceeds zero, the IoT platform transmits a signal with a value of one to the microcontroller. Upon receiving a signal of "1" from the IoT platform, the microcontroller establishes a connection to the power supply of the electrical equipment, therefore granting those within the designated vicinity the ability to operate said equipment. The findings of this study indicate that the implemented Internet of Things (IoT) system effectively operates and activates the electrical equipment upon the detection of individuals in the designated region by the YOLOv3 algorithm.

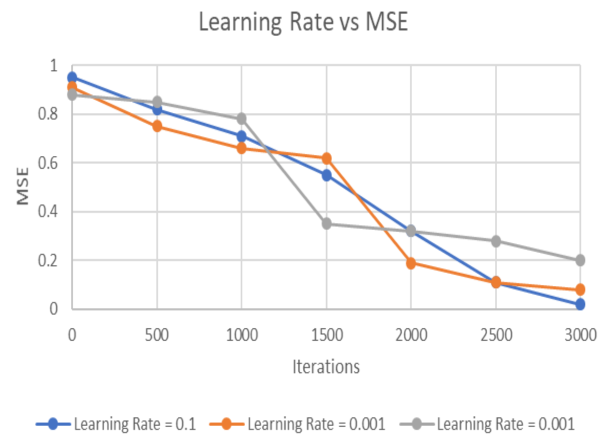

Fig. 6. Learning Rate based MSE analysis

The findings of this study indicate that the Internet of Things (IoT) system under consideration has the capability to deactivate the power supply of electrical equipment in the absence of individuals within a designated region. The implementation of this Internet of Things (IoT) system has the potential to significantly reduce both cost and energy consumption associated with the operation of electrical equipment. In forthcoming times, the suggested methodology would encompass comprehensive modelling of Internet of Things (IoT) and intelligent energy systems, with an additional use in robotics domains to facilitate the advancement of Industry 4.0.

5. Conclusion

This study presents a novel Internet of Things (IoT) architecture that utilises deep learning algorithms for the purpose of energy regulation in smart buildings, specifically focusing on electrical equipment systems. The deep learning approach utilised in this study is implemented using the YOLOv3 flourished classification method. The IoT system under consideration regulates the functioning of electrical equipment by detecting the presence of individuals inside a designated region. This is done with the aim of reducing expenses and energy use associated with such electrical equipment. To validate the efficacy of the proposed Internet of Things (IoT) system, three distinct test scenarios involving varying quantities of individuals have been established. Moreover, the Internet of Things (IoT) system has the capability to autonomously deactivate the power supply to electrical devices in the event that there are no individuals present inside the designated region. The implementation of a closed-loop Internet of Things (IoT) topology has the potential to boost investments in the context of industry 4.0. Furthermore, the suggested Internet of Things (IoT) system has the potential to be used in many applications that rely on recognition and control, therefore warranting further investigation in future research endeavours. Additionally, the proposed methodology will be used on various devices with the aim of reducing energy inefficiency and minimising expenses inside smart grid systems.

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