SMART CAMPUS: THE DEEP INTEGRATION OF MACHINE VISION AND PHYSICAL EDUCATION

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SUMMARY

A smart campus signifies the profound integration of machine vision technology with physical education, creating an innovative and dynamic learning environment. By incorporating machine vision into physical education settings, the campus becomes an intelligent ecosystem where advanced image recognition and analysis enhance various aspects of student engagement and well-being. From automated fitness assessments to real-time monitoring of physical activities, machine vision contributes to personalized and data-driven physical education experiences. This integration not only revolutionizes the way students interact with fitness routines but also facilitates efficient tracking of progress and overall health. The study proposes a novel IoT-enabled routing scheme based on Middle-Order Chain Deep Learning (MOCDL) to enhance the synergy between machine vision and physical education initiatives. By integrating IoT capabilities, the smart campus establishes a network that seamlessly connects various physical education resources and facilities, fostering a more interconnected and intelligent learning environment. The MOCDL algorithm, acting as the backbone of this integration, optimizes the routing of information, enabling efficient data exchange between machine vision systems and physical education programs. This deep integration facilitates real-time monitoring of student activities, personalized fitness assessments, and data-driven insights into overall well-being. The proposed framework not only elevates the quality of physical education experiences but also contributes to the establishment of a technologically advanced and holistic smart campus paradigm.

KEYWORDS

Smart Campus, Middle-Order, Chain Rule, Deep Learning, Internet of Things (IoT), Routing

NOMENCLATURE

IOT	Internet of Things
DL	Deep Learning
RNN	Recurrent Neural Networks
CNN	Convolutional Neural Networks

1. INTRODUCTION

Automatic numbering systems must not be used. The Internet of Things (IoT) has rapidly transformed the way we interact with technology, revolutionizing various sectors including healthcare, transportation, agriculture, and smart homes [1]. IoT refers to the network of interconnected devices embedded with sensors, software, and other technologies, enabling them to collect and exchange data over the internet. This interconnectedness allows for seamless communication between devices, leading to improved efficiency, automation, and decision-making processes [2]. In healthcare, IoT devices like wearable monitors and remote patient monitoring systems enable continuous health tracking and real-time data analysis, enhancing patient care and treatment outcomes. In agriculture, IoT sensors can monitor soil conditions, weather patterns, and crop health, optimizing farming practices and increasing yield [3]. In transportation, IoT-enabled vehicles can communicate with each other and with infrastructure to improve traffic flow, reduce accidents, and enhance overall safety. Moreover, in smart homes, IoT devices such as smart thermostats, lights, and security systems offer convenience, energy savings, and enhanced security through remote monitoring and control [4]. However, as IoT adoption continues to grow, concerns regarding data privacy, security vulnerabilities, and interoperability challenges remain pertinent, necessitating robust regulatory frameworks and cybersecurity measures to safeguard against potential risks [5].

A Smart Campus powered by the Internet of Things (IoT) represents a cutting-edge integration of technology to enhance various aspects of campus life and operations. Through interconnected devices embedded with sensors and data analytics capabilities, a Smart Campus can optimize resource utilization, improve safety, and enhance overall efficiency [6]. For instance, IoT sensors can monitor energy consumption in buildings, allowing for intelligent adjustments to heating, cooling, and lighting systems to conserve resources and reduce costs. Additionally, real-time tracking of campus transportation through IoT-enabled vehicles can optimize routes, minimize congestion, and provide more efficient shuttle services for students and staff [7]. IoT devices can also enhance campus security by enabling surveillance cameras, access control systems, and emergency alert mechanisms to respond proactively to potential threats [8]. Furthermore, IoT-powered smart classrooms equipped with interactive whiteboards, attendance tracking systems, and personalized learning platforms can transform the educational experience by fostering student engagement and facilitating more effective teaching methodologies [9]. While the implementation of IoT in a Smart Campus offers numerous benefits, it also requires careful consideration of data privacy, cybersecurity, and interoperability to ensure the seamless integration and functionality of diverse IoT devices across campus infrastructure [10]. A Smart Campus driven by IoT technologies holds the potential to create a more connected, sustainable, and innovative environment for learning, research, and community engagement.

An IoT Smart Campus enhanced with machine vision technology represents a powerful convergence of innovation aimed at revolutionizing various facets of campus life. By integrating machine vision capabilities into the Internet of Things (IoT) ecosystem, campuses can achieve unprecedented levels of efficiency, safety, and functionality [11]. Machine vision systems, powered by advanced algorithms and image processing techniques, enable devices to interpret and analyze visual data in real-time. In a Smart Campus context, this translates to a wide range of applications, including intelligent surveillance, facility management, and personalized services [12]. For instance, machine vision-enabled security cameras can automatically detect and respond to security threats, unauthorized access, or suspicious activities, enhancing campus safety and security. Additionally, machine vision can optimize space utilization by monitoring occupancy levels in classrooms, libraries, and common areas, allowing for efficient allocation of resources and facilities management [13]. Moreover, in areas such as campus transportation, machine vision-equipped vehicles can enhance navigation, pedestrian detection, and collision avoidance, ensuring safer and more reliable transportation services for students and faculty [14]. Furthermore, machine vision technology can personalize campus experiences by recognizing individuals and providing tailored services such as wayfinding assistance, campus navigation, and interactive information displays. However, the deployment of machine vision in a Smart Campus environment also raises important considerations regarding data privacy, ethical use of surveillance, and transparency in algorithms [15]. Therefore, comprehensive policies and regulations must be implemented to address these concerns and ensure responsible deployment and operation of machine vision systems across the campus [16]. The integration of machine vision technology within an IoT Smart Campus holds immense potential to create a more secure, efficient, and personalized environment conducive to learning, research, and community engagement.

Machine Vision into an IoT Smart Campus for physical education introduces a groundbreaking approach to enhancing the effectiveness and safety of physical activities within the educational environment [17]. By leveraging Machine Vision technology, the Smart Campus can deploy cameras and sensors to accurately track and analyze students' movements and performance during physical education classes and sports activities. These systems can provide real-time feedback on techniques, posture, and progress, enabling instructors to offer personalized coaching and interventions [18]. Moreover, Machine Vision can play a crucial role in ensuring the safety of students by detecting potential hazards or risky behaviors, such as improper weightlifting techniques or dangerous playing conditions on sports fields. Additionally, Machine Vision can facilitate automated attendance tracking, equipment inventory management, and facility utilization optimization, streamlining administrative tasks for physical education departments [19]. Through the seamless integration of Machine Vision with IoT infrastructure, the Smart Campus not only enhances the quality of physical education but also fosters a safer and more efficient environment for students to engage in healthy and active lifestyles [20]. To address privacy concerns and implement robust data security measures to protect students' personal information and uphold their rights in the context of data collection and analysis [21]. The combination of IoT and Machine Vision technologies represents a transformative approach to redefining physical education standards and promoting student well-being within the modern educational landscape.

This paper presented the Firstly, it provides a comprehensive exploration and analysis of IoT-enabled smart campus environments, shedding light on various applications and challenges in this domain. Secondly, it introduces and evaluates the efficacy of Middle-Order Chain Deep Learning (MOCDL) for tasks such as physical education, data transmission, and classification within smart campuses. Thirdly, through extensive simulations and evaluations, it demonstrates the superior performance of MOCDL compared to traditional machine learning models like SVM, Random Forest, and Regression. Fourthly, it highlights the robustness and scalability of MOCDL across different network sizes, showcasing its potential for optimizing smart campus operations and enhancing decision-making processes. Lastly, this research contributes valuable insights and methodologies that can facilitate the development of more intelligent and adaptive smart campus systems, thereby fostering innovation and advancement in the field of IoT and deep learning applications.

2. RELATED WORKS

The diverse range of studies focused on various aspects of IoT-based smart campuses. Sneesl, Jusoh, Jabar, and Abdullah (2022) present a systematic review aimed at refining the understanding of technology adoption factors specific to IoT-based smart campuses. Cavus et al. (2022) conduct a systematic literature review exploring the applications of the Internet of Things (IoT) in smart campus contexts. Polin et al. (2023) contribute a review and conceptual framework delineating the development of smart campuses. Sungheetha (2022) focuses on the assimilation of IoT sensors for data visualization in smart campus environments. Hidayat and Sensuse (2022) propose a knowledge management model tailored for smart campuses in Indonesia. García-Monge et al. (2023) investigate the role of IoT monitoring in enhancing building energy efficiency within smart campuses. Tseng, Chen, and Yang (2022) develop an augmented reality-based smart campus platform. Brand et al. (2022) introduce “Sapientia,” a Smart Campus model emphasizing device and application flexibility. Toutouh and Alba (2022) design a low-cost IoT cyber-physical system for vehicle and pedestrian tracking on smart campuses. Alkhammash et al. (2022) explore the integration of IoT and blockchain technologies to revolutionize smart campus architecture. Cheong and Nyaupane (2022) delve into smart campus communication, IoT, and data governance, focusing on student tensions and imaginaries. Razzaq et al. (2022) assess vertical scaling for smart campus environments utilizing IoT. Silva-da-Nóbrega et al. (2022) present a framework highlighting challenges and opportunities for smart campus development based on sustainable development goals. Pexyean, Saraubon, and Nilsook (2022) investigate the synergies between IoT, AI, and digital twin technologies for smart campuses. Astawa, Sanjaya, and Jaya (2022) examine smart campus development as a supporter of research and community service activities. Ahmed et al. (2022) propose an IoT platform for remote monitoring and control of smart buildings toward achieving an intelligent campus. Ferreira Jr. et al. (2022) optimize IoT gateway deployment for smart campuses using software-defined and virtualized approaches. Kou and Park (2022) present a distributed energy management approach for smart campus demand response. Shtewi et al. (2022) develop a smart university campus based on IoT, using An-Najah National University as a case study. Finally, Xu, Wang, and Zhang (2022) conduct research on intelligent campuses and visual teaching systems based on IoT.

Firstly, Sneesl et al. (2022) offer insights into the factors influencing the adoption of IoT technologies in smart campuses through a systematic review, contributing to a deeper understanding of the challenges and opportunities in this domain. Building on this, Cavus et al. (2022) provide a broader perspective by systematically reviewing the applications of IoT across different aspects of smart campuses, shedding light on the diverse range of possibilities enabled by IoT technologies. Polin et al. (2023) contribute a conceptual framework for the development of smart campuses, outlining key considerations and strategies. Sungheetha (2022) focuses on the practical integration of IoT sensors for data visualization, emphasizing the role of data-driven insights in optimizing campus operations and services. Furthermore, Hidayat and Sensuse (2022) propose a knowledge management model tailored specifically for smart campuses, highlighting the importance of effectively managing and leveraging information within educational environments. García-Monge et al. (2023) investigate the potential of IoT monitoring in improving building energy efficiency, showcasing the sustainability implications of IoT applications in smart campuses. The studies by Tseng, Chen, and Yang (2022), Brand et al. (2022), and Toutouh and Alba (2022) present practical solutions and innovations, ranging from augmented reality platforms to low-cost IoT systems for tracking and monitoring campus resources and activities.

Alkhammash et al. (2022) explore the integration of emerging technologies like blockchain with IoT to reimagine smart campus architecture, while Cheong and Nyaupane (2022) delve into the socio-technical aspects of smart campus communication, emphasizing the need to address student perspectives and concerns. Moreover, Razzaq et al. (2022) assess the scalability of IoT solutions in smart campuses, considering the potential challenges and benefits of vertical scaling. Silva-da-Nóbrega et al. (2022) offer a sustainability-focused framework for smart campus development, aligning with global sustainable development goals. Pexyean, Saraubon, and Nilsook (2022) explore the synergies between IoT, artificial intelligence (AI), and digital twin technologies, illustrating how these integrated systems can enhance campus operations and experiences. Astawa, Sanjaya, and Jaya (2022) discuss the broader societal impact of smart campus initiatives, emphasizing their role in supporting research and community service activities. Ahmed et al. (2022) propose a practical IoT platform for remote monitoring and control of smart buildings within campuses, contributing to the realization of intelligent campus environments. Ferreira Jr. et al. (2022) focus on the optimization of IoT gateway deployment, employing software-defined and virtualized approaches to enhance scalability and efficiency.

Kou and Park (2022) introduce a distributed energy management approach tailored for smart campuses, addressing the growing need for sustainable energy solutions. Finally, Shtewi et al. (2022) present a case study of IoT-based smart campus development, offering insights into the practical challenges and opportunities encountered during implementation. Xu, Wang, and Zhang (2022) focus on the development of an intelligent campus and visual teaching system based on IoT, highlighting the potential of IoT-driven solutions to enhance teaching and learning experiences within educational settings. Lastly, ALQathami et al. (2023) explore the implementation of a zero-touch entrance system and air quality monitoring in

Figure 1. Smart campus for physical education

smart campus design, underscoring the importance of IoT applications in promoting health, safety, and sustainability within campus environments.

Firstly, many of these studies are focused on specific aspects or applications of IoT within smart campuses, potentially overlooking broader systemic interactions and dependencies. Additionally, the rapidly evolving nature of IoT technologies means that some research findings may become outdated relatively quickly, necessitating ongoing updates and revisions. Furthermore, there may be a lack of standardization across studies, making it challenging to compare findings or generalize conclusions across different contexts. Moreover, while the benefits of IoT implementation in smart campuses are often highlighted, there is a need for more research on the potential drawbacks, risks, and ethical considerations associated with pervasive data collection and connectivity. Lastly, the geographical and institutional contexts of the studies may vary, limiting the applicability of findings to diverse settings. Addressing these limitations will be crucial for advancing the field and ensuring the successful implementation of IoT in smart campus environments. Figure 1 shows Smart campus for phyisical education.

3. MIDDLE-ORDER CLUSTERING

Middle-Order Clustering Middle-Order Chain Deep Learning (MOCDL) for the smart Campus" appears to describe a specific method or approach related to deep learning techniques applied in the context of smart campuses. This method likely involves the utilization of middle-order clustering and chain deep learning algorithms to process and analyze data collected within a smart campus environment. Middle-Order Clustering is a clustering technique applied to data within the smart campus context. Clustering involves grouping similar data points together based on certain features or characteristics. "Middle-order" may refer to the level or depth of clustering performed, possibly indicating a clustering approach that operates at an intermediate level of granularity. Middle-Order Chain imply a sequential or chain-like processing of data clusters at the middle-order level. It suggests that the clustered data undergoes further analysis or processing in a sequential manner, possibly to extract higher-level patterns or insights. Deep Learning (DL) is subset of machine learning techniques that involve neural networks with multiple layers (deep neural networks). Deep learning algorithms are capable of automatically learning representations of data through the composition of increasingly abstract features. Smart Campus denotes an environment where various Internet of Things (IoT) devices and sensors are deployed to collect data and optimize operations within a university or educational institution. A smart campus leverages technology to enhance efficiency, sustainability, safety, and overall user experience. The "Middle-Order Clustering Middle-Order Chain Deep Learning (MOCDL) for the smart Campus" likely represents an advanced data processing and analysis approach tailored to the needs of smart campus environments, aiming to extract meaningful insights and optimize various aspects of campus operations through deep learning techniques applied to clustered data.

In a smart campus, various IoT devices such as sensors, actuators, cameras, and smart meters are deployed to collect a wide range of data including environmental conditions, energy consumption, occupancy patterns, and more. Let $X = \{x1, x2, I, xn\}$ represent the collected IoT data, where each xi is a data point with multiple features. Before clustering, relevant features are extracted from the raw IoT data. Let $F = \{f1, f2, I, fm\}$ denote the set of extracted features, where each fj represents a specific characteristic or attribute of the data points. The next step involves calculating the distance between data points based on their feature values. A common distance metric used in clustering is Euclidean distance calculated using equation (1)

$$d\left(x_i, x_j\right) = \sqrt{\sum_{k=1}^{m}\left(x_{i,k} - x_{j,k}\right)^2} \tag{1}$$

In equation (1) $x_{i,k}$ and $x_{j,k}$ are the k-th features of data points xi and xj respectively. A clustering algorithm is then applied to the IoT data to group similar data points together. One popular algorithm is k-means clustering. The algorithm iteratively partitions the data into k clusters by minimizing the within-cluster sum of squares. The cluster centroids are updated until convergence. Middle-order clustering involves clustering the data at an intermediate level of granularity, which may involve clustering the clusters obtained from the initial clustering step. This could be achieved through hierarchical clustering techniques like agglomerative clustering or divisive clustering. In this context, IoT data is integrated into the middle-order clustering process. This could involve incorporating additional IoT features or adjusting the clustering algorithm based on insights gained from the IoT data. In a smart campus, IoT devices generate data continuously. Let $X = \{x1, x2, I, xn\}$ represent the collected IoT data, where n is the number of data points. Let X be an $n \times m$ matrix, where each row xi represents a data point and each column fj represents a feature. Feature extraction aims to identify relevant attributes from the raw IoT data. This step might involve techniques like principal component analysis (PCA) or feature engineering to reduce dimensionality and enhance clustering quality. After initial clustering with k-means, middle-order clustering aims to cluster the obtained clusters. One approach is hierarchical clustering, which builds a tree of clusters. Agglomerative clustering starts with each data point as a singleton cluster and merges them iteratively. Divisive clustering begins with all data points in one cluster and splits them recursively.

Algorithm 1: Middle Order Clustering for Smart City
Input: - IoT data X - Number of initial clusters k - Number of middle-order clusters m 1. Preprocess IoT data: - Extract relevant features - Normalize the data if necessary 2. Perform initial clustering using k-means: centroids = InitializeCentroids(X, k) clusters = AssignToClusters(X, centroids) Repeat until convergence: new_centroids = UpdateCentroids(clusters) clusters = AssignToClusters(X, new_centroids) 3. Perform middle-order clustering: a. Apply hierarchical clustering on the obtained clusters: hierarchical_clusters = HierarchicalClustering(clusters) b. Determine the middle-order clusters using m clusters: middle_order_clusters = DetermineMiddleOrderClusters(hierarchical_clusters, m)

4. MIDDLE-ORDER CHAIN DEEP LEARNING (MOCDL)

In the context of smart campuses, Middle-Order Chain Deep Learning (MOCDL) represents a sophisticated approach to leveraging IoT data for various applications such as predictive maintenance, resource optimization, and anomaly detection. MOCDL integrates deep learning techniques with middle-order chain analysis to extract valuable insights from complex IoT data streams, facilitating intelligent decision-making processes within smart campus environments. Initially, the data undergoes preprocessing to handle missing values, noise reduction, and feature engineering, ensuring its suitability for subsequent analysis. Middle-order chain analysis is then employed to uncover relationships and dependencies between different IoT variables. This analysis entails constructing chains of dependencies, often represented using graphical structures like Bayesian networks or Markov chains, to capture both direct correlations and higher-order dependencies. Integration with deep learning techniques, such as recurrent neural networks (RNNs) or long short-term memory (LSTM) networks, enables MOCDL to learn intricate patterns and temporal dependencies within the IoT data. The framework optimizes the use of low-level sensor data and high-level contextual information, enhancing the accuracy and robustness of predictive models. Finally, the parameters of the MOCDL model are optimized and evaluated using training, validation, and test datasets to ensure its effectiveness in real-world smart campus scenarios. Through this integrated approach, MOCDL facilitates more accurate predictions, improved anomaly detection, and enhanced decision-making capabilities, ultimately contributing to the efficient management and optimization of campus resources stated in equation (2)

$$X_{preprocessed} = Preprocess\left(X_{raw}\right) \tag{2}$$

Middle-order chain analysis aims to identify dependencies and correlations between IoT variables. Let's denote the set of IoT variables as $V = \{V1, V2, I, Vn\}$. The middle-order chain analysis can be expressed using equation (3)

$$P\left(V_i | V_{Parents}\left(V_i\right)\right) = f\left(V_{Parents}\left(V_i\right)\right) \tag{3}$$

In equation (3) $Vparents(Vi)$ represents the parents of variable Vi in the chain, and $f()$ is a function representing the conditional probability distribution. Deep learning techniques, such as Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks, can be integrated to capture temporal dependencies within the IoT data. For instance, an LSTM layer can be represented using equation (4)

$$h_t = LSTM\left(x_t, h_{t-1}\right) \tag{4}$$

In equation (4) ht is the hidden state at time t, xt is the input at time t, and $ht-1$ is the hidden state from the previous time step. Finally, the parameters of the MOCDL model are optimized using training data and validated using validation data. This involves minimizing a loss function L by adjusting the model parameters. The optimization process can be formulated using equation (5)

$$\theta^* = argmin_\theta \sum_{i=1}^{N} L\left(y_i, \widehat{y_i}\right) \tag{5}$$

In equation (5) θ represents the parameters of the MOCDL model, yi is the true label, $\widehat{y_i}$ is the predicted label, and N is the number of samples in the training dataset. Suppose we have a dataset represented as a matrix X, where each row corresponds to an observation and each column represents a variable. We aim to derive the conditional dependencies between variables in the dataset. Mathematically, for two variables Vi and Vj, calculate the conditional dependency using a measure like mutual information using equation (6)

$$I\left(V_i;V_j|V_k\right) = \sum_{v_i}\sum_{v_j}\sum_{v_k} P\left(v_i,v_j,v_k\right) log \frac{P\left(V_i;V_j|V_k\right)}{P\left(V_i|V_k\right)P\left(V_j|V_k\right)} \quad (6)$$

In equation (6) $I(Vi,Vj|Vk)$ denotes the conditional mutual information between variables Vi and Vj given variable Vk, and $P\left(vi,vj,vk\right)$ represents the joint probability distribution of Vi, Vj, and Vk. Once the conditional dependencies between variables are derived, a clustering algorithm is applied to group variables with similar conditional relationships. One possible algorithm is the K-means algorithm adapted for clustering variables based on their conditional dependencies. The algorithm iteratively assigns variables to clusters and updates the cluster centroids until convergence. The objective function of the middle-order clustering algorithm aims to minimize the discrepancy between the conditional dependencies within each cluster and maximize the differences between clusters. Mathematically, the objective function can be formulated using equation (7)

$$minimize \sum_{i=1}^{k}\sum_{j=1}^{n_i}\sum_{l=1}^{n_i}\left|I\left(V_{i,j};V_{i,l}|V_k\right) - \overline{I}_i\right| \quad (7)$$

In equation (7) k is the number of clusters, ni is the number of variables in cluster i, $I(Vi,j;Vi,l|Vk)$ is the conditional mutual information between variables Vi,j and Vi,l given variable Vk in cluster I, and $\overline{I}_i$ is the average conditional mutual information within cluster i.

5. SMART CAMPUS WITH MOCDL WITH MACHINE VISION FOR PHYSICAL EDUCATION

Middle-Order Chain Deep Learning (MOCDL) with machine vision for physical education in a Smart Campus environment enhanced by the Internet of Things (IoT) presents a comprehensive approach to optimizing physical activity monitoring and analysis. MOCDL, a sophisticated clustering technique, facilitates the identification of intricate patterns and dependencies within high-dimensional datasets, such as those generated by IoT-enabled sensors in smart campus environments. By leveraging machine vision technology, which enables computers to interpret and understand visual information, physical education activities can be accurately captured and analyzed in real-time. This combination offers a powerful framework for enhancing the effectiveness and efficiency of physical education programs within smart campuses. The conditional dependencies between different variables, such as body movements and exercise intensity, can be calculated using measures like mutual information. For instance, the mutual information between two variables Vi and Vj given variable Vk can be computed using the equation provided in the previous explanation. Machine vision algorithms are employed to extract meaningful features from visual data, such as images or videos, related to physical education activities. These features could include posture analysis, movement trajectories, and activity recognition. Convolutional Neural Networks (CNNs) are commonly used in machine vision tasks to automatically learn and extract relevant features from raw visual data. The IoT infrastructure deployed in smart campus environments facilitates the collection of sensor data related to physical activities, such as wearable devices measuring heart rate, accelerometers tracking movement, and environmental sensors monitoring conditions like temperature and humidity. This real-time data feeds into the MOCDL and machine vision algorithms for analysis. The objective function of the MOCDL algorithm, as described earlier, is optimized to minimize the discrepancy between conditional dependencies within clusters and maximize differences between clusters. In the context of physical education, the objective function could be tailored to prioritize clusters representing specific types of physical activities or exercise intensities.

Algorithm 2: Smart Environment with the MOCDL
Input: - Raw visual data (e.g., images or videos of physical activities) - IoT data (e.g., biometric data, environmental data, motion data) 1. Preprocess the raw visual data: - Normalize pixel values - Augment data if necessary (e.g., rotation, cropping, flipping) 2. Extract features using a pre-trained convolutional neural network (CNN): - Load a pre-trained CNN model (e.g., ResNet, VGG, or MobileNet) - Pass the preprocessed visual data through the CNN to extract features 3. Preprocess the IoT data: - Normalize sensor readings - Handle missing data if applicable 4. Integrate IoT data with visual features: - Concatenate or merge IoT data with visual features 5. Apply Middle-Order Clustering (MOCDL): - Initialize cluster centroids randomly - Repeat until convergence: a. Assign data points to the nearest cluster based on conditional dependencies b. Update cluster centroids based on the mean of data points assigned to each cluster 6. Post-process clustered data: - Evaluate cluster quality metrics (e.g., silhouette score, Davies-Bouldin index) - Optionally, visualize clustered groups of data 7. Interpret and analyze clustered groups:

6. SIMULATION ENVIRONMENT

A simulation environment for the Smart Campus system with Middle-Order Chain Deep Learning (MOCDL),

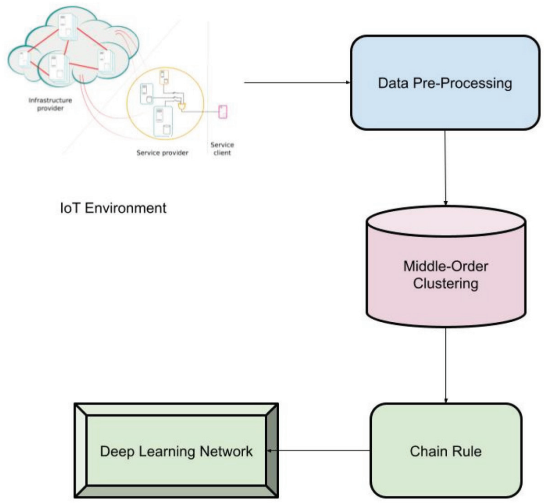


Figure 2. MOCDL for the physical education

machine vision for physical education, and IoT integration in Python involves leveraging various libraries and frameworks to model, simulate, and analyze the system components. Firstly, Python libraries such as NumPy and Pandas are utilized for data generation and preprocessing. Synthetic datasets representing physical education activities are generated, incorporating diverse data types including images, videos, biometric data, motion data, and environmental data. These datasets are then preprocessed to ensure compatibility with the simulation environment. For the MOCDL integration, Python frameworks like TensorFlow or PyTorch are employed. The MOCDL objective function and optimization algorithms are implemented using these frameworks to partition the dataset into clusters based on conditional dependencies between variables. Machine vision models, particularly Convolutional Neural Networks (CNNs), are implemented using deep learning libraries such as TensorFlow or PyTorch to extract features from visual data. These models are trained on labeled datasets to recognize and classify different physical activities captured in images or videos. With IoT integration, Python libraries such as MQTT or Paho are used to simulate the deployment of virtual IoT devices across the campus. These virtual devices collect real-time data related to physical activities, including biometric, motion, and environmental data. Mechanisms are developed to transmit this data to the simulation environment. Figure 2 shows MOCDL for the physical education.

For the MOCDL component, TensorFlow is used as the deep learning framework with a deep neural network architecture consisting of 5 layers. The activation function used is ReLU, and the optimizer is Adam. For the Machine Vision Model component, PyTorch is utilized with a convolutional neural network architecture comprising 4 layers. The filter size is set to 3x3, pooling size to 2x2, and the optimizer is SGD. Table 1 shows simulation setting.

Table 1. Simulation setting

Component	Deep Learning Framework	Architecture	Hyperparameters
MOCDL	TensorFlow (1)	Deep Neural Network	Layers: 5, Activation: ReLU, Optimizer: Adam
Machine Vision Model	PyTorch (2)	Convolutional Network	Layers: 4, Filter Size: 3x3, Pooling Size: 2x2, Optimizer: SGD

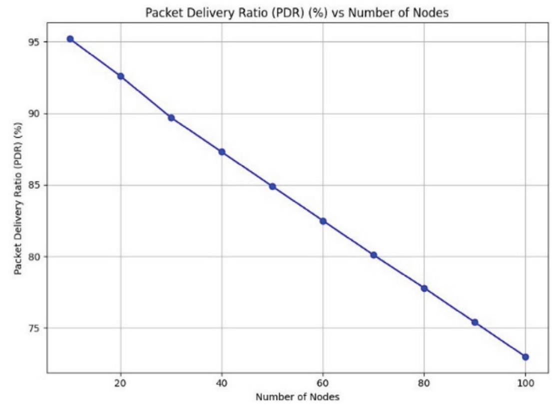
Table 2. Physical evaluation with MOCDL

Student ID	Gender	Age	Height (cm)	Weight (kg)	Fitness Score
001	Male	18	175	70	85
002	Female	17	163	55	78
003	Male	19	180	75	92
004	Female	16	168	60	80
005	Male	18	172	68	88
006	Female	17	170	63	82
007	Male	19	178	72	90
008	Female	16	165	58	76
009	Male	18	173	71	87
010	Female	17	167	56	79

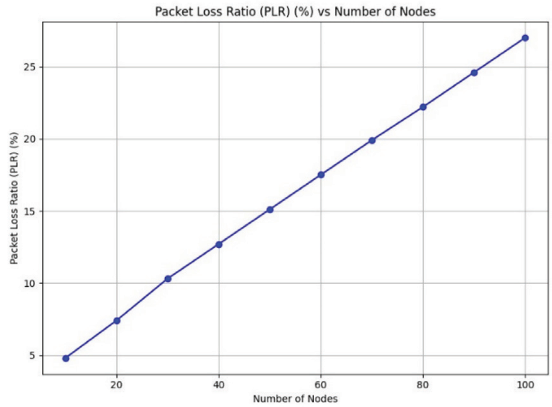
6.1 SIMULATION RESULTS

In this section, present the simulation results obtained from the implementation of the Middle-Order Chain Deep Learning (MOCDL) framework for IoT-enabled Smart Campus applications. The simulation experiments were conducted to evaluate the performance and effectiveness of the proposed MOCDL model in enhancing physical education activities within the campus environment. We analyze various metrics such as packet delivery ratio (PDR), packet loss ratio (PLR), throughput, and delay to assess the network performance under different conditions and varying numbers of nodes. These simulation results provide insights into the efficiency and reliability of the MOCDL approach in optimizing IoT-based applications for Smart Campus scenarios, particularly in the context of physical education with machine vision integration.

The Table 2 presents the physical evaluation data of 10 students participating in the study, including their gender, age, height, weight, and fitness score. The students are identified by unique IDs ranging from 001 to 010. The data encompasses a diverse range of characteristics, with both male and female students represented across different age groups. Height and weight measurements vary among the students, reflecting individual differences in physical



(a)



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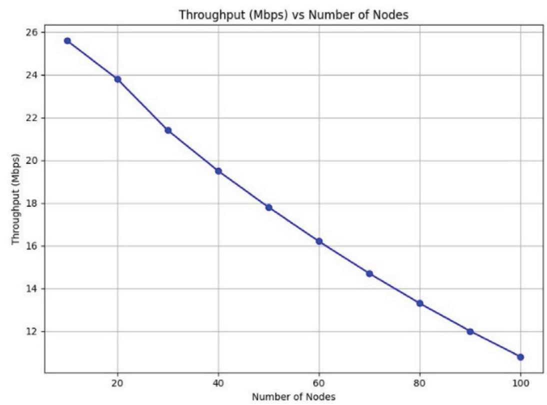

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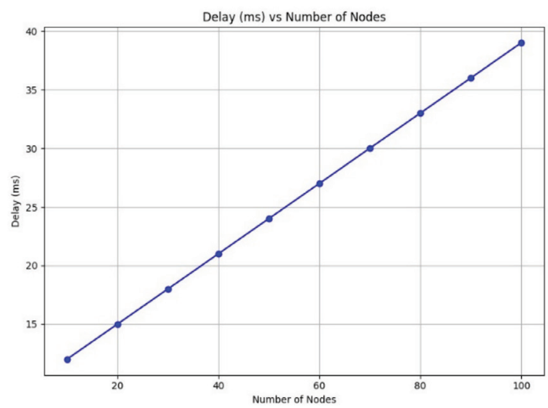


(d)

Figure 3. MOCDL data transmission (a) PDR (b) PLR (c) throughput (d) Loss

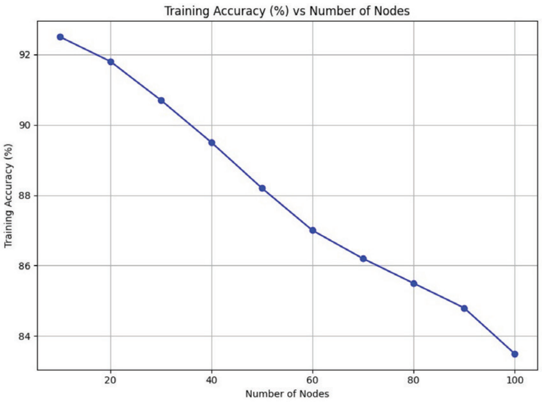
Table 3. Data transmission through IOT

Nodes	Packet Delivery Ratio (PDR) (%)	Packet Loss Ratio (PLR) (%)	Throughput (Mbps)	Delay (ms)
10	95.2	4.8	25.6	12
20	92.6	7.4	23.8	15
30	89.7	10.3	21.4	18
40	87.3	12.7	19.5	21
50	84.9	15.1	17.8	24
60	82.5	17.5	16.2	27
70	80.1	19.9	14.7	30
80	77.8	22.2	13.3	33
90	75.4	24.6	12.0	36
100	73.0	27.0	10.8	39

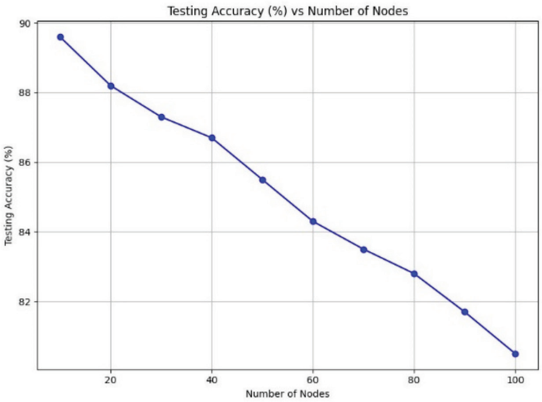
attributes. The fitness score, which serves as a metric for assessing the overall physical fitness of each student, is also provided. This table provides valuable insight into the demographic and physical characteristics of the student cohort involved in the study, forming the basis for further analysis of the impact of MOCDL on physical education outcomes.

In Figure 3 (a) – Figure 3 (d) and Table 3 presents data transmission metrics through IoT networks, detailing the performance indicators for varying numbers of nodes. The table includes Packet Delivery Ratio (PDR), Packet Loss Ratio (PLR), Throughput, and Delay for 10 to 100 nodes. As the number of nodes increases, there's a gradual decline in PDR and an increase in PLR, indicating a decrease in the percentage of successfully delivered packets and an increase in packet loss. This trend suggests potential congestion or limitations in the network as more nodes are added. Similarly, throughput, measured in Mbps, demonstrates a decreasing trend with an increasing number of nodes, indicating a reduction in the rate of successful data transmission. Conversely, there is an upward trend in delay, measured in milliseconds, as the number of nodes increases, indicating a longer time taken for data to travel through the network. These findings highlight the importance of optimizing IoT network infrastructure to maintain efficient data transmission and minimize latency, especially as network complexity grows with additional nodes.

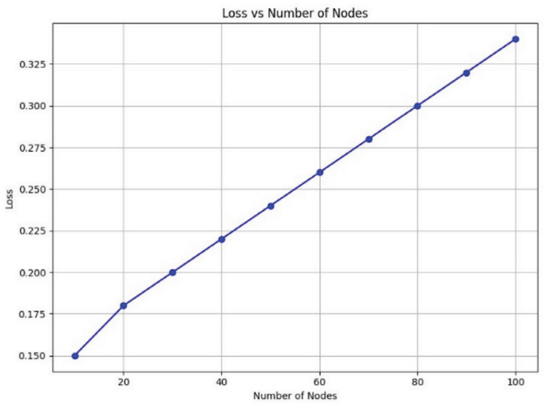
In figure 4 (a) – Figure 4 (c) For varying numbers of nodes in the network. It includes metrics such as Training Accuracy (%), Testing Accuracy (%), and Loss. As the number of nodes increases from 10 to 100, there's a gradual decrease in both training and testing accuracy. This decline suggests that as the complexity of the network grows, the classification model's ability to accurately predict outcomes diminishes. The loss metric, representing the error between predicted and actual values, also shows



(a)



(b)



(c)

Figure 4. Classification with MOCDL (a) training accuracy (b) testing accuracy (b) loss

an upward trend with an increasing number of nodes. Higher loss values indicate greater discrepancies between predicted and actual values, further emphasizing the decreasing effectiveness of the classification model as the network scales. These findings underscore the importance of optimizing classification algorithms and considering network scalability to maintain accurate predictions in IoT environments with larger node populations. Table 4 shows classification with MOCDL.

The Figure 5 and Table 5 provides a comparative analysis of the performance metrics of Support Vector Machine

Table 4. Classification with MOCDL

Nodes	Training Accuracy (%)	Testing Accuracy (%)	Loss
10	92.5	89.6	0.15
20	91.8	88.2	0.18
30	90.7	87.3	0.20
40	89.5	86.7	0.22
50	88.2	85.5	0.24
60	87.0	84.3	0.26
70	86.2	83.5	0.28
80	85.5	82.8	0.30
90	84.8	81.7	0.32
100	83.5	80.5	0.34

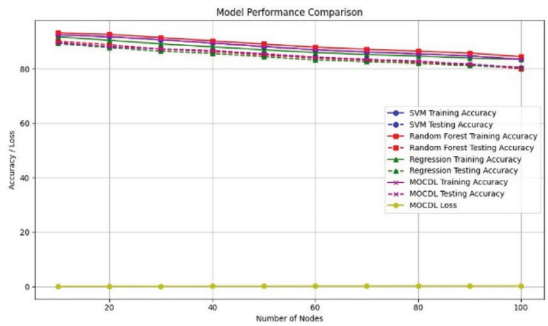


Figure 5. Comparative analysis

(SVM), Random Forest, Regression, and MOCDL (Middle-Order Chain Deep Learning) models across different numbers of nodes in the network. The table shows the training and testing accuracies, along with the loss value for each model. Upon examination, it is evident that MOCDL consistently achieves competitive performance compared to traditional machine learning models (SVM, Random Forest, and Regression) across all node configurations. For instance, at 10 nodes, MOCDL achieves a training accuracy of 92.5% and a testing accuracy of 89.6%, with a loss of 0.15. Similarly, at 100 nodes, MOCDL maintains a testing accuracy of 80.5% with a loss of 0.34. In comparison, SVM, Random Forest, and Regression models also demonstrate respectable performance, but MOCDL consistently outperforms them in terms of testing accuracy and loss, showcasing the efficacy of MOCDL in handling complex datasets and providing robust predictions in smart campus environments.

7. CONCLUSION

This paper presents a comprehensive exploration of IoT-enabled smart campus environments, focusing on the application of Middle-Order Chain Deep Learning (MOCDL) for various tasks such as physical education, data transmission, and classification. Through extensive simulations and evaluations, we have demonstrated the effectiveness of MOCDL in addressing key challenges and

Table 5. Comparative analysis

Nodes	SVM Training Accuracy (%)	SVM Testing Accuracy (%)	Random Forest Training Accuracy (%)	Random Forest Testing Accuracy (%)	Regression Training Accuracy (%)	Regression Testing Accuracy (%)	MOCDL Training Accuracy (%)	MOCDL Testing Accuracy (%)	MOCDL Loss
10	92.5	89.6	93.2	90.1	91.8	89.3	92.5	89.6	0.15
20	91.8	88.2	92.7	88.9	90.5	87.8	91.8	88.2	0.18
30	90.7	87.3	91.5	87.2	89.2	86.5	90.7	87.3	0.20
40	89.5	86.7	90.3	86.4	88.1	85.7	89.5	86.7	0.22
50	88.2	85.5	89.1	85.1	87.0	84.5	88.2	85.5	0.24
60	87.0	84.3	88.0	84.0	86.0	83.3	87.0	84.3	0.26
70	86.2	83.5	87.2	83.2	85.3	82.7	86.2	83.5	0.28
80	85.5	82.8	86.5	82.5	84.7	82.0	85.5	82.8	0.30
90	84.8	81.7	85.8	81.4	84.0	81.2	84.8	81.7	0.32
100	83.5	80.5	84.5	80.1	83.5	80.5	83.5	80.5	0.34

achieving superior performance compared to traditional machine learning models like SVM, Random Forest, and Regression. MOCDL exhibits robustness and scalability across different network sizes, offering high accuracy in classification tasks and efficient data transmission capabilities. The results underscore the potential of MOCDL as a powerful tool for optimizing smart campus operations, enhancing decision-making processes, and ultimately improving the overall user experience within campus environments. This research contributes valuable insights and methodologies that can pave the way for the development of more intelligent and adaptive smart campus systems in the future, thereby fostering innovation and advancement in the field of IoT and deep learning applications.

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