Machine Learning for Internet of Things: Applications and Discussions

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***Abstract*—The Internet of Things (IoT) has emerged as a powerful network paradigm, connecting diverse devices and generating vast amounts of data. Analyzing these data offers valuable insights and enables the development of sophisticated systems to improve our lives. However, processing the data from various devices with diverse backgrounds and requirements remains an important challenge. To process heterogeneous data, machine learning (ML) has emerged as a promising solution for managing large-scale and high-dimensional data in IoT networks. ML can support IoT networks by providing meaningful insights across various applications. Despite the immense potential of ML in the IoT landscape, several challenges remain. In this paper, we investigate the application of ML and discuss the considerations for employing ML in the context of IoT networks.**

***Index Terms*—Internet of Things, machine learning, applications.**

I. Introduction

The Internet of Things (IoT) has emerged as a promising network paradigm, encompassing various interconnected devices [1], [2]. The devices in IoT networks, such as sensors, gadgets, appliances, and actuators, generate a continuous stream of heterogeneous data. Collecting and extracting meaningful insights from these data via thorough analysis enables the developing of sophisticated systems that enrich our lives [3]. However, processing the data from various devices with diverse backgrounds and requirements remains an important challenge [3], [4]. Therefore, using advanced tools is essential to extract meaningful insights from the substantial volume of raw data.

To handle heterogeneous data, machine learning (ML) has attracted increasing interest in handling large-scale and high-dimensional data [5]. An ML-based approach is expected to support the IoT network implementation as a significant volume of data generated by IoT devices needs to be analyzed intelligently. Furthermore, ML can enhance the performance of the IoT system by providing insights for various IoT applications [1], [3].

Despite the immense potential of ML in the IoT landscape, several challenges remain [6]. Limited computational resources on IoT devices often hinder the implementation of complex ML models. Additionally, ensuring data privacy and security within the network poses another significant concern. Addressing these challenges requires innovative research and development of efficient and secure ML algorithms specifically tailored for the resource-constrained environment of IoT networks. In this paper, we first explore the applications of ML in IoT networks to show ML can be adopted in various systems and provide discussions on the usage of ML.

The rest of this paper is structured as follows. Section II briefly provides an overview of IoT architecture and ML. Section III presents various applications in ML-based IoT networks. Section IV provides discussions on ML-based IoT systems. Finally, the conclusion is shown in Section V.

II. Overview on Internet of Things and Machine Learning

A. Internet of Things

Fig. 1 depicts the three-layer architecture of the Internet of Things: perception, network, and application [2], [7], [8].

- Perception layer (a.k.a. device/physical layer): It encompasses IoT devices such as sensors, actuators, smart cameras, and connected appliances. Employing diverse sensors and actuators, these devices act as transducers, translating physical world phenomena into digital data streams subsequently ingested by the network layer for further elaboration and analysis.
- Network layer: It sits at the heart of the IoT architecture, serving as a critical conduit between data acquisition (perception layer) and its utilization (application layer). IoT gateways act as data intermediaries, efficiently channeling sensor-generated information toward the network layer via diverse communication protocols, including WiFi, LTE, Bluetooth, and Zigbee.
- Application layer: This layer analyzes and processes data to provide services, make informed decisions, and generate outputs upon receiving data. These outputs are then transmitted to the perception layer via the network layer. The application layer can provide various applications, such as monitoring the manufacturing process, predicting traffic congestion, and measuring patients' blood pressure.

In addition, there are some additional players to consider. The edge computing layer is becoming increasingly important in IoT architectures. Edge computing allows data to be processed and analyzed closer to the devices where it is generated, which can reduce latency and improve performance [9]. Security is a major concern in IoT systems, in which IoT devices and systems are secure from unauthorized access and cyberattacks [10], [11]. Interoperability is also important in IoT, where IoT devices and systems from different vendors can work together seamlessly.

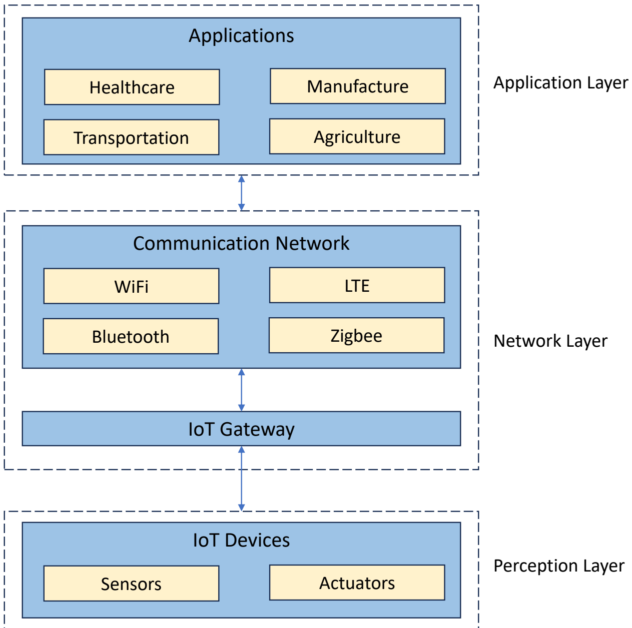

Fig. 1. The general architecture of IoT.

B. Machine Learning

ML, a subset of artificial intelligence (AI), equips computers with the ability to learn and adapt from data without direct instructions. It does this by analyzing data and identifying patterns and relationships. Thens, it can use them to perform predictions or decisions on new data. There are four main approaches to ML: supervised, unsupervised, semi-supervised, and reinforcement learning.

- Supervised learning: Models are trained with a labeled dataset [12]. This means each input in the training data is associated with its corresponding correct output. By grasping the underlying patterns in labeled data, supervised learning models can apply their knowledge to make accurate predictions or classifications in new, unseen data.
- Unsupervised learning: The algorithms are trained with unlabeled data, and the system tries to learn the patterns and structure from the data without explicit guidance on the correct outputs [8]. The goal is to describe the distribution of data and the relationship between variables without distinguishing between observed and predicted variables. Unsupervised learning is used for grouping tasks such as recommendation systems, categorizing customers, and conducting targeted marketing [13], [14].
- Semi-supervised learning: A semi-supervised learning algorithm utilizes labeled and unlabeled data to train a model. The presence of labeled data allows the algorithm to learn from explicit input-output pairs, while the unlabeled data enables the algorithm to explore and learn the underlying structure of the data [14].
- Reinforcement learning (RL): RL distinguishes itself from other learning paradigms by eschewing explicit guidance from labeled data or dedicated teachers [15], [16]. Instead, it navigates its path to optimal behavior through an iterative process of trial-and-error interaction with the environment, guided solely by reward signals [9]. Driven by the receipt of rewards following its actions within the environment, the agent's primary objective is to learn an optimal policy that maximizes the total cumulative reward over time.

III. Applications

While the potential applications of ML in IoT are vast, its impact can be most observed in several key areas as follows.

A. Smart Healthcare

ML can be used to enhance the performance of healthcare systems. By leveraging ML, healthcare providers can deliver more efficient, effective, and personalized care to their patients [1]. Continuous health data acquisition via wearable sensors provides a plethora of real-time bio-signals for analysis by ML models. This enables the development of novel algorithms capable of identifying early-stage disease signatures, tailoring treatment strategies to individual patient profiles, and predicting potential health risks based on data-driven insights [17]. The authors in [18] proposed the blood pressure measurement system. Blood pressure data was collected from the network, and regression models such as support vector machine (SVM) and k-nearest neighbor (KNN) were used to forecast blood pressure values. The work in [19] proposed a smart framework for home rehabilitation for poststroke patients. The data was collected by multiple nodes in the network. The system performance was evaluated by ML approaches such as a random tree, random forest (RF), logistic regression, Naive Bayes, and multilayer perceptron. In [20], the authors proposed a lightweight real-time health monitoring system utilizing an IoT sensor to track the patient's heart rate and oxygen saturation. Their system leverages the Autoregressive Integrated Moving Average (ARIMA) algorithm for predicting future patient measurements.

B. Smart Manufacturing

Smart manufacturing aims to increase production line efficiency through predicting system variables accurately and fast [2]. In [21], leveraging big data machine learning, the authors developed a quality prediction model and evaluation system for intelligent manufacturing. They employed an extreme learning machine neural network trained with a particle swarm optimization algorithm. In [22], employing fault detection and classification techniques, the authors aimed to optimize yield and product quality within smart semiconductor manufacturing environments. Their approach utilized a convolutional neural network to analyze status variable identification data and assess wafer conditions, boosting system performance while reducing self-learning time through domain knowledge integration and real-time updates of monitoring rules. In [23], the proposed algorithm automatically identified and extracted distinct groups within the dissolved gas data. The authors employed principal component analysis (PCA) to optimize data representation for subsequent clustering. Subsequently, the k-means algorithm, leveraging Euclidean distance as its similarity metric, was utilized to identify and categorize data points into distinct clusters.

C. Smart Homes

Smart homes leverage the power of ML to enhance their functionality and provide various benefits, such as predictive maintenance, energy efficiency, and personalized comfort. In the domain of residential load monitoring, the work [24] introduced a novel home appliance classification model that optimizes energy management and identifies potentially faulty devices. The Long Short-Term Memory (LSTM)-based model, trained on the Plug-Load Appliance Identification Database (PLAID) dataset, demonstrates proficiency in classifying 16 distinct appliances. In [25], the authors tackled the challenge of optimizing energy consumption and maximizing occupant comfort by proposing a novel Open Connectivity Foundation (OCF)-based prediction-assisted optimal control framework. This framework leverages the power of LSTM inference models deployed on edge IoT devices, enabling proactive and real-time control decisions.

D. Smart Agriculture

As populations surge and climatic fluctuations intensify, coupled with a finite resource base, ensuring adequate food security for current populations poses a formidable challenge to agricultural systems across all nations. In [26], the authors proposed the extreme learning machine (ELM)-powered architecture to predict the dew point temperature by leveraging SVM and ANN methods. In [27], ML models such as extreme gradient boosting (XGBoost), support vector regression (SVR), cubist, RF, multi-layer perceptron (MLP), KNN, gaussian process, and multivariate adaptive regression splines were utilized to predict the accurate yield gap in wheat production. In [28], the authors tested the performance of ML methods, including M5 rules, M5 model trees, genetic programming, SVR, and KNN to predict rainfall. Statistical results revealed that RBFNN achieved the best performance.

E. Smart Transportation

Traffic congestion, a prevalent issue in urban areas, is worsening due to increasing vehicles [4], [29]. Thus, route optimization is needed to minimize traffic congestion. In [30], an ML-based algorithm was proposed to predict traffic congestion. The proposed method utilized logistic regression to analyze traffic data and predict congestion on specific paths. This allowed for proactive notification of vehicles intending to travel on congested paths well in advance, enabling them to choose alternative routes. In [31], the deep RL algorithm was applied for a dynamic and uncertain vehicle routing problem. To address the uncertainty in customer demand forecasting, this solution leverages a real-time decision support system powered by a deep neural network with dynamic attention. The system frequently monitors evolving customer demand trends through a partial observation Markov decision process.

IV. Discussions

Although ML-based IoT networks bring great convenience, security issues need to be discussed. To enable near-zero-delay services, ML models are increasingly deployed at the edge of the network, closer to the data source and end devices [32], [33]. However, edge servers and devices often face resource limitations, including limited computational power and storage capacity. Additionally, they are susceptible to malicious attacks, particularly distributed denial-of-service (DDoS) attacks that can overwhelm resources and disturb network services [6]. Existing security methods often generate excessive computational and communication loads, rendering them impractical for resource-constrained end devices [2], [33]. These demanding workloads can drain device batteries, slow processing, and hinder connectivity, ultimately compromising the user experience. Therefore, lightweight security mechanisms can be discussed for resource-constrained devices.

The distributed and heterogeneous nature of data poses significant challenges for parallel training of machine learning models. To enable parallel training, federated learning (FL) emerges as a viable solution, offering several advantages [34]. Notably, FL minimizes communication overhead, preserves data privacy, and maintains high model quality, making it well-suited for parallel training in resource-constrained environments. However, edge nodes present significant challenges due to their heterogeneous bandwidth, varying computing capabilities, and unevenly distributed data across different nodes [35]. This heterogeneity necessitates careful consideration and adaptation when implementing federated learning at the edge.

The rapid decision-making capabilities of ML-based IoT networks, often occurring within milliseconds and exceeding the speed of human oversight, raise potential ethical concerns [36], [37]. Novel design principles must be considered to ensure responsible and ethical development. In addition, ML models must be transparent and accountable. Explainable AI is crucial to understand how decisions are made and avoid perpetuating biases in the data [38]. Overall, ML is the engine powering the IoT revolution. The applications will proliferate as algorithms become more sophisticated and computational resources evolve. The key lies in responsible development, addressing ethical concerns, and ensuring equitable access to the benefits of this powerful technology.

V. Conclusion

This paper investigates the application of ML and discusses the considerations for employing ML in the context of IoT networks. First, we provided the fundamentals of IoT and ML. Subsequently, we presented the applications of ML in IoT networks, such as smart healthcare, smart manufacturing, smart homes, smart agriculture, and smart transportation. In addition, we demonstrated several discussions, including security vulnerabilities, difficulties in parallel training, and ethical concerns. More applications and issues of ML-based IoT networks can be investigated for future research.

ACKNOWLEDGMENT

This research was supported by the MSIT (Ministry of Science and ICT), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2024-RS-2022-00156353) supervised by the IITP (Institute for Information & Communications Technology Planning & Evaluation).

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