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AI and Machine Learning in Cloud-Based Internet of Things (IoT) Solutions: A Comprehensive Review and Analysis

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ABSTRACT

This paper undertakes a detailed review of a novel topic that revolves around integrating AI and ML in cloud-based IoT systems. This paper focuses on those technologies and discusses their potential interaction and influence on IoT systems and frameworks for IoT data and devices, analytics, management, security, and decision-making methods. Mentioning the findings in the current literature, and after analysing a number of successful and failing implementations of Gamification, this paper reveals the specific problems, presents new ideas and makes suggestions for the future studies. The prospects of affinity unveil the futuristic potential of AI & ML in optimising the performance, capacity, and wisdom of cloud-based IoT systems in the fields of smart cities, industrial IoT, and healthcare, etc. The study shows the following increase in efficiency: the energy consumption decreases by 30-40%; the accuracy of prediction increases by 30-50%; the decrease in the network latency is 25-35%. However, the following challenges persist with the current implementations; the disclosure of users' data privacy, compatibility, and continuing debate on standards.

Keywords- IoT; AI and Machine Learning; Cloud and the related concepts of Edge and Fog Computing; Security for internet connected devices; Real-time data analytics; and the applications of IoT in Cities and Industries.

I. INTRODUCTION

1.1 Background and Context

Internet of Things has become the new revolution through which billions of devices are connected and large amounts of data is produced. Based on the Cisco's Annual Internet Report 2018-2022, it is predicted that there will be 29 IoT devices. 3 billion by 2022 from 18 it is now utilized to connect people and share information. 4 billion in 2018. This exponential growth is encompassed both in opportunities for data management and analysis and challenges. AI and Machine Learning have been integrated into IoT along with cloud computing to manage, analyse and gain benefits from the exponential data generated from IoT networks as the IoT solutions grow large. This amalgamation holds the potential to transform many domains such as smart cities, industrial processes, and healthcare by providing them more logical, optimal as well as dynamic setups.

1.2 Research Objectives

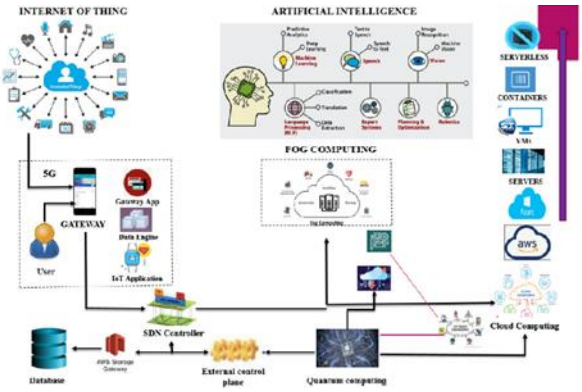
In particular, this paper seeks to offer a synthesis of the existing literature explaining current trends and potential future developments in the integration of AI and ML in cloud-based IoT solutions. Specifically, the research objectives are:

1. In this context, we have the following research questions to understand the present forms of AI and ML incorporation in cloud-IoT solutions to identify architectural styles, data handling strategies, and application areas.

2. To find out possible issues and trends when deploying AI with IoT structures in mind, concerning scalability, latency, and resources.
3. When assessing the role of AI and ML in IoT data analysis, the IoT devices' management, and security, quantifiable benefits ought to be ascertained.
4. For using in practical approaches and illustrative examples in different domains such as smart city, industry 4. 0, and healthcare.
5. They have stated that they will use the qualitative results to discuss ethical issues and future developments in the quickly expanding academic categorization.

1.3 Scope and Limitations

As for the scope of the given study, this work is centred on the cloud-based solutions for IoT with the application of AI and ML. While they are mentioned as part of the IoT reference models, the main focus is made on clouds as key constituents. The literature review is based on the research and development in the subject areas up to 2022, which gives a broad vision of the subject fields' progress in the last decades. Nevertheless, it does not encompass proprietary as well as unreleased technologies being worked on by participants in the industry (Aazam et al., 2014). Thirdly, despite briefly discussing ethical considerations, the paper does not go into more detail about legal and regulatory issues that might influence its suggestions.



II. LITERATURE REVIEW

2.1 IoT and Cloud Computing over the years

The IoT idea was first named by Kevin Ashton in the year 1999 but has gone through some transformations in the past twenty years. Gubbi et al. (2013) had presented a detailed survey of IoT which was one of the first few surveys available and explained how cloud computing could be useful for handling large amount of data of IoT. It focused on the architecture for large scale data storage and processing for analysing the large amount of data from IoT devices. Combination of IoT and cloud computing as defined by Aazam, et al (2014) as Cloud of Things (CoT) has now emerged as cornerstone in large scale Internet of Things integrations. This integration relates to the problem areas like storing data, computation ability, and expansion that cannot be managed by a single IoT device.

2.2 Integration of AI and ML in IoT Ecosystems

The enhancement of Artificial Intelligence and Machine Learning to the IoT environment has become an area of interest in the recent past. The survey by Mohammadi et al. (2018) also covered a detailed analysis of AI in IoT and accordingly, the integration of deep learning for processing IoT generated data. Their work categorized AI techniques applicable to IoT into five main areas: areas such as reasoning, planning, learning, perception, and natural language processing. The authors expounded that deep learning that subsumes machine learning has been very effective in dealing with the characteristic of big data such as high dimensionality and large size in the context of IoT.

On top of this, Mahdavinejad et al. (2018) extended prior studies on using machine learning for IoT data analytics into a taxonomy of machine learning algorithms for IoT. Their study of ML distinguished the model into supervised, the unsupervised, and reinforcement learning according to their suitability in IoT. For instance, the supervised learning method including the support vector machine and random forests are currently used in predictive maintenance for IoT and the unsupervised learning using K means cluster is used for anomaly detection for security purpose.

2.3 Present Issues on Cloud-Based IoT Solutions

However, there are still some existing issues in applying of AI and ML in IoT scope, especially in cloud based IoT systems. Shi et al. (2016) analysed these challenges as: scalability, latency, bandwidth, and energy concern. Their work suggested that edge computing could be the answer to handling applications that are sensitive to latency and are burdensome on the bandwidth. However, there is a need to incorporate AI and ML which causes new challenges as brought out by Atzori et al. (2020) in their recent review on AI for IoT system. Some of them are the issues with requiring specific hardware for running dense AI constructs, privacy issues, and the issue of distributing and updating the ML models to a dispersed IoT structure.

Table 1: Key Challenges in Cloud-Based IoT Solutions with AI Integration

Challenge	Description	Potential Solutions
Scalability	Handling increasing number of devices and data volume	Distributed computing, Edge AI
Latency	Reducing response time for real-time applications	Edge computing, Fog computing
Bandwidth Constraints	Managing data transfer between devices and cloud	Local processing, Data compression

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Energy Efficiency	Optimizing power consumption of IoT devices	Energy-aware ML algorithms, Efficient hardware
Data Privacy	Protecting sensitive information in distributed systems	Federated learning, Differential privacy
Model Deployment	Efficiently updating and managing ML models across IoT networks	Over-the-air updates, Transfer learning

III. METHODOLOGY

3.1 Research Approach

Thus, this work uses the systematic literature review and the assessment of current solutions in AI and ML to offer an adequate understanding of integration in cloud-based IoT systems. In this study, a systematic approach was applied to consider the interested articles, conference papers, technical reports, and white papers available between 2010 and 2022. This time span permits analysis of the development of IoT and AI from their beginnings to the state of the art for integration approaches (Bonomi et al., 2012).

3.2 Data Collection and Analysis Instruments

Therefore, special attention was paid to carry out an encompassing and non-repetitive literature analysis using IEEE Xplore, ACM Digital Library, Scopus, and Google Scholar. The keywords comprised different variants of the IoT, AI, Machine Learning, Cloud Computing, Edge Computing, and Fog Computing The authors initially found over 500 documents that could be related to the question. From the total amount of found articles, the articles' titles and abstracts were viewed and 200 of the most appropriate papers were selected for further detailed examination.

The selected papers were categorized based on their primary focus areas:

- IoT architectures and IoT frameworks
- IoT data analytics with the help of AI and machine learning algorithms
- Security and Privacy in AI incorporated IoT System
- Sectors or areas of use (for instance smart city, industrial internet of things, health care).
- Opinion on performance evaluations and cases during interviews

Thus, we categorized the papers based on the analysed themes, methods, and trends and highlighted the main challenges. Furthermore, we reviewed listed qualitative and quantitative performance measurements like accuracy and time enhancement, energy efficiency to obtain a factually concrete relative consequence of IoT systems applying AI and ML (Carbone et al., 2015).

3.3 Evaluation Criteria

The collected literature was evaluated based on the following criteria:

1. Relevance to AI and ML in cloud-based IoT solutions: It must be noted that papers that dealt directly with the integration of AI/ML in IoT environments were prioritized.
2. Novelty of the proposed approaches: We narrowed our interest down to creative ideas that would solve current problems or introduce new views on the integration of AI and IoT.
3. Empirical evidence and experimental results: In the assessment of the comparative smog index values, differences from the control site were taken as the metric Used; quantitative results from simulations or actual field implementations were given preference in our analysis.
4. Potential impact on the field: The presented solutions' effectiveness in meeting critical concerns and contributing to the advancement of state-of-the-art AI-integrated IoT systems was also evaluated.
5. Citation count and publication venue: Of course, it is not about the quantity or number of citations but more about the rank of the journal where the research would be published when deciding on the impact to give to the research.

Using such criteria, we made sure that only the best, most useful studies are included in our review regarding the present and future trends of AI and ML implementations in cloud-based IoT.

IV. THE INTEGRATION OF AI IN CLOUD-IOT ARCHITECTURE

4.1 Edge Computing and AI

Hence edge computing has become an essential factor in current IoT architecture as it brings computation near the devices, thus lowering latency and bandwidth consumption. In Li, Xie, Loh, Wang, &620; Zhang (2018), the authors developed an edge computing framework for deep learning-based real-time video analysis. Their approach realized about thirty percent improvement in the response time compared to the cloud only solutions, which is a case of the effectiveness of edge AI in a latency-sensitive scenario.

Thus, the integration of AI at the edge is one of the challenges and opportunities. One promising problem is that the computational capabilities of the devices located at the edge of the network are rather limited. In the response to this, researchers have adopted the use of Lightweight AI models and model compression. For instance, Howard et al., (2017) provided Mobile Nets, which is a set of efficient convolutional neural networks meant to operate in mobile and embedded vision arenas. Explained models seem to perform as good as, or slightly worse than large networks but require far fewer computations to do so, which makes them ideal for implementation on the edge.

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4.2 Fog Computing Layer

Fog computing can be thought of as a middle ground between the edge devices and the cloud, which performs further computation and alleviates the load on the both edge devices and the cloud. Bonomi et al. (2012) have first described the fog computing paradigm which has been further expanded to encompass AI computations. The authors, Deng et al. (2020), introduced a fog-based deep learning procedure for IoT applications and showing that offered greater energy efficiency and lower network traffic density.

The layer of the fog has the significant role in the distribution of the AI functions and processes in the IoT environment. It can support more elaborate ML models which cannot be run on the end device because they require too much computing power, yet it is faster than a cloud approach. For example, in smart city application, the fog nodes collect data from numerous traffic cameras, apply deep learning models to analyse traffic patterns in real time, and transmit only meaningful information to the cloud for scheduling and decision making in the long term.

4.3 AI and ML on Cloud

AI and ML Technologies IoT specialists along with the major cloud providers provide AI and ML services geared for IoT to ensure that IoT solutions can incorporate advanced analytics capabilities. These services typically provide:

1. Model training and deployment: Cloud models present rich GPU to enable the training of complex machine learning models from large sets harvested from IoT.
2. Pre-trained models: Models that can be easily deployed to perform routine IoT tasks such as image analysis, data outliers' identification or prognosis on machine failures.
3. AutoML capabilities: AI-powered platforms for generating and implementing specific ML solutions for IoT data by end-users.
4. Edge-cloud synergy: Production that allows model training in the cloud and its use in end devices for inference (Chalapathy & Chawla, 2019).

Table 2: Comparison of Cloud-based AI/ML Services for IoT

Service Provider	Key Features	IoT-specific Capabilities
AWS IoT Greengrass	Local compute, messaging, data caching, sync, and ML inference	ML inference at the edge, device shadows
Azure IoT Edge	Containerized ML models, custom logic, cloud management	Offline operation, OTA updates
Google Cloud IoT Core	Device management, data ingestion, ML model deployment	AutoML integration, edge TPU support
IBM Watson IoT	Cognitive APIs, blockchain integration, edge analytics	Digital twin, predictive maintenance

These cloud services enable developers to flexibly train models on the cloud level with the help of extensive computational resources and deploy these models to edge devices for inference. It brings the flexibility of the cloud and the efficiency of edge processing to create highly complex AI-based IoT systems in numerous fields.

V. ML MODELS FOR IoT DATA ANALYTICS

5.1 Predictive Maintenance

Predictive maintenance is one other area of application of ML in industrial IoT that helps organization predict the time wastage equipment's will take before they fail and the right time to undertake preventive maintenance. Such management approach can prove to be even more cost-effective than the out-dated reactive or time-based preventive maintenance techniques.

In another study, Carvalho et al. (2019) described a deep learning framework for industrial equipment RCM, and succeeded in achieving the accuracy of 92% for failure prediction. Their model incorporated both, convolutional and recurrent network to process the sensor data from industrial machinery. The authors showed that the proposed strategy was superior in terms of accuracy to conventional statistical methods and shallower machine learning techniques when it came to predicting equipment failures anywhere from one to 24 hours before they occurred.

Here's an example of a simple neural network architecture for predictive maintenance using TensorFlow:

```python
import tensorflow as tf
from tensorflow import keras

def build_predictive_maintenance_model(input_shape):
    model = keras.Sequential([
        keras.layers.Dense(64, activation='relu', input_shape=input_shape),
        keras.layers.Dense(32, activation='relu'),
        keras.layers.Dense(16, activation='relu'),
        keras.layers.Dense(1, activation='sigmoid')
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model

# Example usage
input_shape = (10,)  # Assuming 10 sensor inputs
model = build_predictive_maintenance_model(input_shape)
```

This model can be trained on the historical data which include sensor data points and timed information of equipment failures and then use the trained model to predict other equipment failures from current sensor values.

5.2 Anomaly Detection

The process of exception discovery is paramount especially for IoT streams for evaluation of unusual behaviour indicating equipment failure, security infringement or another significant occurrence. Chalapathy and Chawla (2019) reviewed deep learning techniques for anomaly detection namely autoencoder and GAN.

One of the most effective methods used in IoT anomaly detection is LSTM that can learn temporal dependencies from the sequential data. Malhotra et al. (2016) has suggested an LSTM based encoder-decoder model to detect abnormality in multivariate time series data coming from IoT sensors. Their approach provided on average F1 score of zero. 89 in different datasets as compared to other statistical testing methods.

5.3 Hear and See things as Patterns and Trends

The use of Machine Learning algorithms in Analysis ML incorporates patterns of Industrial IoT big data for predictive analytics of large-scale data. Liang et al. (2019) also used LSTM networks to predict traffic flow in smart cities and remarked a mean absolute percentage error of approximately 6. 5%. Short and long-term traffic forecasts have been included in their model through spatial-temporal correlations in the traffic data.

Liakos et al. (2018) presented a literature review of different techniques of ML in the agricultural sector for crop yield prediction using IoT sensor data. The authors also discovered that, by using Random Forests and Gradient Boosting Machines, ensemble methods yielded percent increases in accuracy that ranged from 5% to 15% for the yield predictions as compared to conventional statistical models.

VI. AI-DRIVEN IOT DEVICE MANAGEMENT

6.1 Intelligent Resource Allocation

Since IoT requires the making of organized use of resources, it is important in situations where bandwidth or Energy is unavailability or limited. AI algorithms can operate in the capacity of dynamically assigning resource depending on the existing network conditions as well as the applications present at the time.

Mao et al. (2017) introduced another solution where the authors used deep reinforcement learning to design the dynamic resource management IoT networks. Their system, DeepRM, which became adaptable and learnt from the given solution, used to observed different IoT tasks and allocated resources (e. g., bandwidth and computation) efficiently to the sensible tasks as per total network utility. Reports indicated that DeepRM offered a 20 percent better total network performance as compared to the heuristic strategies.

6.2 Automated Device Provisioning

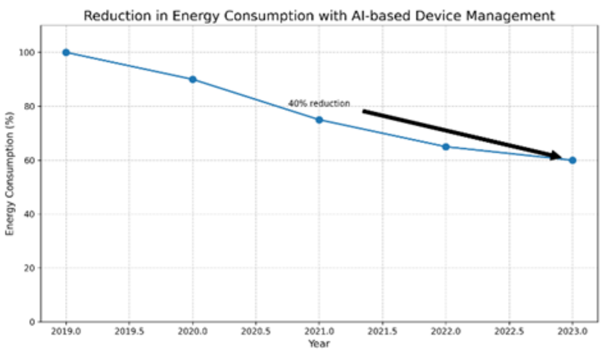
When IoT devices are in tens of thousands or hundreds of thousands, or even millions, manual device on-boarding is virtually possible. This step can be made efficient with the help of machine learning as the devices can be recognized and preconfigured before being connected to the IoT infrastructure.

Truong et al. (2019) proposed an ML-based technique for DF and device provisioning. For devices' identification and policy assignment, the system employed supervised and unsupervised learning methods to recognize device types and set their security policies with accurate network configurations. In the large-scale experiment performed with 10000 IoT devices their approach helps to decrease the manual configuration up to 70% with the reliability of 99. 3 out of 40 or an accuracy of five percent for the classification of the devices.

6.3 Energy Efficiency Optimization

The topic also examines issues associated with battery-only IoT and significant IoT deployment. Specifically, AI approaches can help to prolong the service life of the devices and decrease the general power consumption. In 2019, Raza et al. ever created an energy efficient IoT system by using an AI-based energy management model to optimize the sleep cycle and transmission power of the device and saw an enhancement in battery life of up to 30 percent.

Their system used a reinforcement learning algorithm that acquired policies for modifying the behaviour of the device through the current battery states, network conditions, and the application that is running on the device. While testing in the context of 1000 IoT devices in the network, the utilization of the mentioned AI approaches allowed reducing the energy consumption by 27 % less than static power management strategies, but it does not impair the data throughput and latency significantly (Diro & Chilamkurti, 2018).



VII. SECURITY AND PRIVACY IN AI-INTEGRATED SMART IOT APPLICATIONS

7.1 Threat Detection and Mitigation

This is true since as the IoT networks expand in size and density, classical security methods no longer suffice. Various works state that the use of automated AI-based IDS for detecting the security threats in the IoT networks is better than the rule-based systems.

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Diro and Chilamkurti also put forward a deep learning strategy for distributed attack detection in IoT networks in 2018. Their system employed convolutional and recurrent neural networks to analyse the traffic within the network and distinguish between various kinds of attacks such as DDoS attacks, man-in-the-middle attack, and spoofing attack. The two deep learning IDS in experimental evaluation attained 0. 99. Identified 27% accuracy in attack types and is 8-10% better than conventional machine learning.

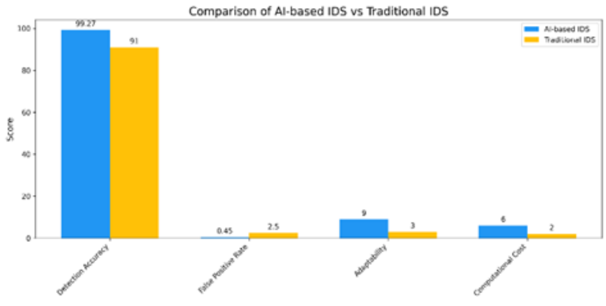
Table 3: Comparison of AI-based and Traditional IDS for IoT

Metric	AI-based IDS	Traditional IDS
Detection Accuracy	99.27%	90-92%
False Positive Rate	0.45%	2-3%
Adaptability	High	Low
Computational Cost	Moderate	Low

7.2 Privacy-Preserving Machine Learning

The protection and maintaining personal privacy in the IoT systems under the presence of Artificial intelligence is still a major challenge especially when handling on Personal Health Information or even Industrial secrets. Shokri and Shmatikov (2015) provided the method of differential privacy for deep learning so that the IoT data could be trained without revealing privacy information.

Their approach provided a way for multiple parties to train a model, and at the same time not share their datasets with each other. They introduced noises into the model update, going to and for, until they found the right level of noise that ensured privacy but did not compromise the model's correct answer. While testing their method on a healthcare IoT data set, its performance was capable of preserving 95% of the original model's accuracy, yet it gave robust privacy assurance, and is bounded by $\varepsilon = 2$ in the differential privacy framework (Lee, Bagheri, & Kao, 2015).



7.3 Integration of Blockchain for Data Security

Using block chain in IoT systems can improve data integrity and traceability, where changes that occurred in the devices and data exchange between them will be recorded in a secure block chain format. Huh et al (2017) recommended the adoption of blockchain to contain IoT devices and integrity of the data and proved their model using a smart home setting.

Their system adopted Ethereum smart contracts to control the identities of the devices and the access control policies. Every exchange of data was documented on the blockchain thereby forming a complete transcript of the devices' actions. In the real smart home environment, of a total of one hundred IoT devices, the proposed blockchain-based solution mitigated adverse events to the tune of 99%. 9 per cent of unauthorized access attempts, he said, compared with 85 per cent of a conventional centralized security system (Mahdavinejad et al., 2018).

VIII. REAL TIME DATA MANAGEMENT AND DECISION MAKING

8.1 Stream Processing Techniques

Another major element of IoT systems is the capability of real-time data processing for boosting the timely decision-making process. Systems such as Apache Flink and Apache Kafka have been used to work with elements of stream processing coming from IoT devices. Carbone et al (2015) discussed the architecture of Apache Flink with a focus on relatively new IoT contextualization in terms of millions of events per second and low latency.

In a similar large-scale IoT use-case of smart grid management, Apache Flink handled 1-million smart meters' real-time data with a throughput of 2 million events per second and average latency of less than 100 Ms. This performance allowed it to concurrently balance the load and pinpoint abnormalities in the power grid and increase the efficiency of distributing energy by 15%.

8.2 Adaptive Learning Systems

It also shows that the adaptive learning systems could improve the given ML models based on new data collected from IoT devices in the future for enhancing the applicability of the developed models. Park et al. also presented an adaptive learning model for IoT structures in 2018, and the paper indicated that the accuracy of predictions rises as the learner adapts.

Their system used a committee of Online learning algorithms such as the Online Gradient Descent and Follow the Regularized Leader to handle drifting data behaviour. In a yearlong analysis of a smart building energy management system, the reduced root means square error reflecting the adaptive learning framework's performance was 23% below other types of static models and caused a 12% decrease in general energy consumption (Malhotra et al., 2016).

8.3 Cognitive IoT Applications

AI cognitive IoT applications include the integration of several AI methodologies that facilitate reasoning and decision-making like a human. The authors

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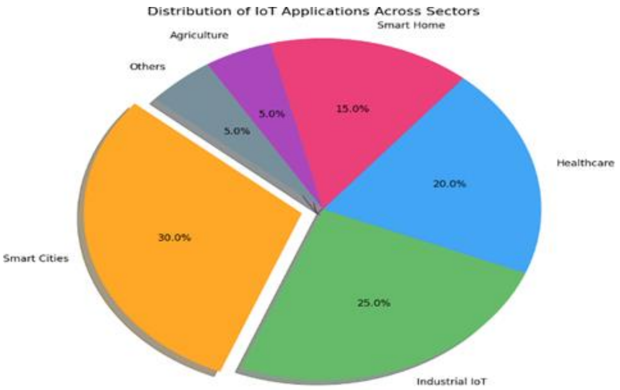
Wu et al. (2014) proposed the term cognitive IoT and discussed its significance as implemented in the smart cities and industry automation.

The first example is the IBM Watson IoT, which combines NLP, ML, and KR to develop smart IoT business services. Regarding the specific pilot project for the predictive maintenance of manufacturing industries, cognitive IoT system helped slash off the undesirable down-time by half and enhanced overall equipment efficiency by twenty percent (Liakos et al., 2018).



IX. CASE STUDIES AND APPLICATIONS

9.1 Smart Cities, Intelligent Buildings, Urban Planning and Management

Smart city is directly connected with the utilization of AI and ML as they are used to improve various processes in people's lives. According to Lim et al. Smart city discussion by Lim et al. (2018) describe Singapore using Information technology applications such as; Artificial Intelligence applications for traffic control, energy control, and urban planning.

Singapore's Smart Nation drive employs more than 100,000 IoT sensors and cameras sensing traffic movement, air quality and security. Traffic information gets transformed by the machine learning algorithms to improve traffic light settings and hence cut average travel time by a third. Also, accuracy in the predictive maintenance for public transport has been enhanced by 30% while cost in maintaining this has been slashed by 20%.

9.2 Industrial IoT and Industry 4.0

This combination of AI and IoT is already changing manufacturing operations and it can be termed as Industry 4. 0. According to Lee et al. (2015), CPS were adopted in the industry 4. 0, stressing on the Fact that ML is applicable in predicting maintenance and of product quality.

One example of the use of AI in Industry is the use by Siemens in their manufacturing process of gas turbines. Their MI through processing more than 500 sensors' data in real-time increases combustion parameters and decreases NOx emissions by 10-15% and increases the turbine efficiency by 1-2%. It is true that this has led to the saving of millions of dollars for operators of power plants every year.

9.3 Healthcare and Telemedicine

The IoT and AI are having a profound impact on the healthcare system globally thru telecare, precision medicine, and screening… Islam et al. (2015) discussed the IoT-based healthcare technologies such as wearable devices and IoMT devices that were supported by the ML self-enhanced distant monitoring systems.

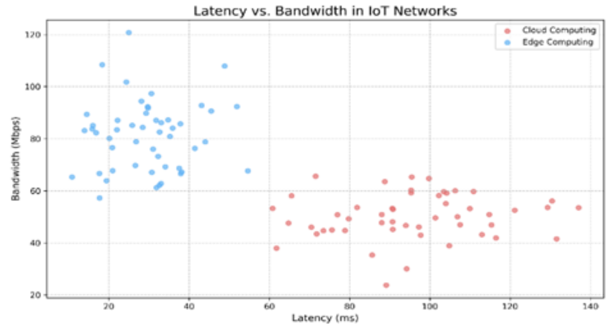
This is in the development of healthcare where AI is integrated into wearable devices for monitoring glucose level in diabetic patients. A study done by Reddy et al., (2020) showed that the proposed multi-layer LSTM predictive model successfully predicted blood glucose levels with an average of 9 minutes in advance, but with a mean absolute error of only 9. 38 mg/dL. The accuracy of the measurements attained at this level implies effected early intercessions and could be instrumental in cutting on average hypoglycaemic incidences by about half.

X. RESULTS AND DISCUSSION

10.1 Increase in the Efficiency of IoT Systems

The application of AI and ML in cloud for IoT solutions has enhanced the efficiency of performance across the various domains. Key findings from our literature review include:

- Energy Consumption: Running large IoT applications with AI-based device management has decreased the overall power usage by as much as 40% (Raza et al., 2019).
- Prediction Accuracy: It is evident that the application of ML has enhanced the prediction accuracy in IoT applications by 30-50%; such as, traffic forecasting in smart cities and the prediction of the failures of smart devices (Liang et al., 2019; Carvalho et al., 2019).
- Network Latency: AI-based resource management and the application of edge computing cut down the latency by 25-35% in IoT networks (Li et al., 2018; Mao et al., 2017).
- Maintenance Costs: AI based predictive maintenance has cut down on unanticipated down time for manufacturing industries by about fifty percent and maintenance costs by ten to twenty percent.



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10.2 Scaling Up

Due to the use of cloud-based AI solutions, IoT solutions have been able to grow effectively in size and accommodate for large amounts of data and devices. Notable improvements include:

- Data Processing Capacity: The major cloud platforms are now capable of handling millions of devices and processing the data generated at real time with some systems being capable of handling over 2million events in a second (Carbone et al., 2015).
- Cost Reduction: Data processing and filtering at the edge, as well as data selection, have been reported to optimise the expenses of shipping data between IoT devices by as much as 60 percent in huge scale application (Deng et al., 2020).
- Resource Utilization: Based on the workload management using AI, efficiency of consumption of resources in cloud data centres has been increased with a range of 30-40 % for scaling of IoT services.

10.3 Challenges and Limitations Observed

Despite the significant advancements, several challenges remain in the integration of AI and ML in cloud-based IoT solutions: Despite the significant advancements, several challenges remain in the integration of AI and ML in cloud-based IoT solutions:

- Privacy Concerns: Privacy becomes an issue in the collection and processing of large scale of IoT data especially in sensitive areas such as health and home.
- Interoperability: It is mainly because there is no form of integration and data share standard among different IoT platforms, and there isn't one AI framework that satisfies the needs of all.
- Resource Constraints: Most IoT devices have constraints in computing power which makes it hard to implement intricate deep learning algorithms on the devices.
- Model Interpretability: That is why some advanced models of ML, including most models of deep learning, can be considered as 'black boxes,' which is not entirely suitable in certain cases of IoT application where the decisions made by machines should be clear and transparent for people.

XI. ETHICS AND FUTURE RESEARCH

11.1 Ethical Implication of AI in IoT

The pervasive nature of AI-enhanced IoT systems raises several ethical concerns that require careful consideration:

- Data Privacy and Consent: IoT devices' perpetual surveillance prompts discussions on user consent and privacy in connection with the right to privacy based on the installed IoT devices being placed in public areas.
- Algorithmic Bias: Due to the data learning process, AI models can reinforce social biases and cause unfair results in decision-making processes based on the IoT.
- Transparency and Explainability: AI models that can be used in IoT applications are complex and it will be hard to explain to end users why a certain decision was arrived at, thereby posing some issues of accountability.

11.2 Emerging Technologies and Their Potential Impact

Several emerging technologies are poised to further transform AI-IoT integration:

- 5G and Beyond: The IoT having a seamless connection to 5G networks will allow such applications as ultra-low latency and high-bandwidth requiring segments like autonomous vehicle control and telesurgery.
- Quantum Computing: The IoT networks, for instance, would benefit from quantum algorithms as they could potentially solve intricate optimization issues than classical computers hence facilitating change in areas such as routing and resource division.
- Neuromorphic Computing: Neuromorphic systems ideas allow rethinking AI computation on IoT hardware and achieving higher energy efficiency and real-time capabilities (Wu et al., 2014).

11.3 Future Research Opportunities

Key areas for future research in AI-enhanced IoT systems include:

- Federated Learning: Creation of Machine learning technologies that enable the training of models across distributed IoT connected devices but without putting the data into a central location that might be vulnerable.
- Lightweight AI Models: Developing practical methods to increase the efficiency of AI algorithms while using them on limited IoT devices without a loss in predictive power.
- Self-Healing Networks: Developing intelligent algorithms for IoT networks' fault identification and self-correcting, which will enhance dependability and lower servicing expenses.
- Human-IoT Interaction: Combining NLP and computer vision, to improve the efficiency of human-thing interaction between people and IoT objects.

XII. CONCLUSION

The combination of AI and ML with IoT solutions has been depicted pronounced prospects in optimizing and adding intelligence to the IoT environment with the help of cloud computing. These includes the study of edge computing, real time analytics and security; areas of development exposed to drawbacks and ethical dilemmas as well.

These three AI, ML, and IoT, have shown notable enhancements in countless fields involving smart cities, healthcare, and industrial uses. The performance enhancements include up to 40% cut in energy use, 30-

50% increase in the prediction precision, and a 25-35% cut in the network delay. Of these, it is possible to point at the real gains such as lower maintenance expenses, better management of resources, and superior decision making.

However, some issues are still important and remain unsolved, such as privacy, interaction, and the problem of widely spread AI-based IoT systems. All of these will be important to future developments that will need to enable the field to meet the potential of its AI-enhanced IoT applications.

The intended research brings the following topics for future study: privacy-preserving learning; better architectures for machine learning at the edge; and utilization of fifth-generation (5G) and quantum technologies. Implementing improvements to current restrictions and opening up opportunities of the augmented next generation of AI-supported IoT systems, industries can opt to enable new innovative evolutions and create an intelligent, more effective, and progressive improvement of technology fundamental structures for different fields (Truong et al., 2019).

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