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ABSTRACT

The Internet of things has emerged as a significant and developing chain paradigm, linking a large number of intelligent objects. Massive amounts of data are produced by IoT systems, which has led to the emergence of ever-more IoT applications and assistance. Human interaction with Computer vision,graphics, natural language processing with the function of speech recognition, and human intelligent control are just a few of the scientific areas where machine learning has had considerable success.

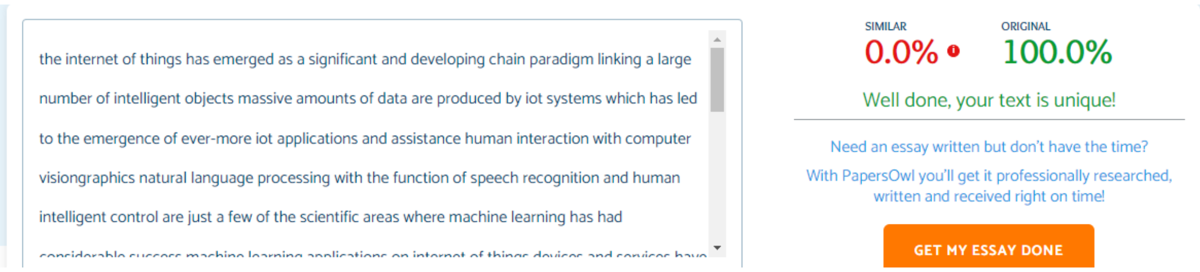
Machine learning applications on internet of things devices and services have become progressively favoured due to their ability to process and analyse data at the edge, enabling real time decision making and lessen the need for sending large amounts of data to the cloud.

Numerous studies and research examine ways and approaches to use machine learning and its methods or techniques to address challenges and issues with routing, traffic engineering, resource allocation, and security in networks , which are the hurdles of IoT systems and its workings.

Moreover, Machine learning is an advanced technology that can solve networking problems, including routing, traffic engineering, resource allocation, and security.

The symbiotic integration of ML and IOT enables users to obtain deep analytics and develop coherent intelligent IoT applications. The major administration of machine learning enabled IoT relevant techniques, including traffic profiling, IoT device recognition, security, edge computing infrastructure, network management and typical IoT devices.

Keywords : Machine Learning, Internet of things[IoT], IoT applications



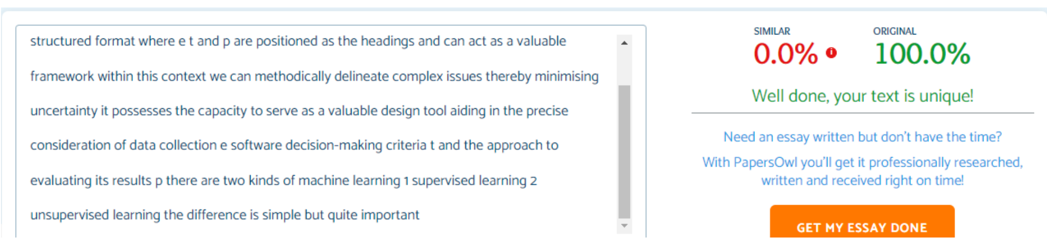
WHAT IS MACHINE LEARNING?

Machine learning is a highly flourishing artificial intelligence branch of computers that utilises this structured format, where E, T, and P are positioned as the headings, and can act as a valuable framework.

Within this context, we can methodically delineate complex issues, thereby minimising uncertainty. It possesses the capacity to serve as a valuable design tool, aiding in the precise consideration of data collection (E), software decision-making criteria (T), and the approach to evaluating its results (P).

There are two kinds of machine learning - **1. Supervised learning**
2. Unsupervised learning
The difference is simple but quite important.

1.1 SUPERVISED LEARNING
The datasets in this category are labelled to train algorithms and predict the accurate outcomes.
1.2 UNSUPERVISED LEARNING



Clustering unlabeled datasets to analyse the algorithm to be used and retrieve the hidden informations and patterns or data groups.

1. WHAT IS IOT?

The Internet of Things systems (IoT) represents a system network of unified smart devices that collectively create an ecosystem, enabling the delivery of intelligent services to users.

IoT has brought numerous convenience to people's lives and the atmosphere. The various applications within the IoT ecosystem offer a range of facilities and services, with one of the most critical advantages being the capability to make rapid decisions for efficient management.

In recent times, machine learning (ML) techniques have played a pivotal role in unlocking the full potential of IoT systems. This paper aims to provide a literature review of the existing literature concerning the integration of ML methods into IoT.

2. CHALLENGES IN IOT

We categorise the challenges faced by IoT systems into two main groups:
1. Fundamental operational challenges
2. Performance related challenges.

3.1 Fundamental Operational Challenges

The core obstacles that have been deep rooted in the system that are defined for specific domains or industry or sectors and must be addressed for effective functioning and working of the devices.

Scalability, reliability and privacy, interoperability are the vital disputes that are addressed in every sector under the fundamental operational challenges.

3.2 Performance Related Challenges

Performance related challenges influence the effectiveness of the working of the system and devices. The impact includes the speed and responsiveness of the IoT systems.

Latency, Network Congestion, Data processing and compression are the major challenges that should have some robust measures to overcome the obstacles.

3. Overview of Machine Learning Applications and issues IoT Systems

Furthermore, we check into how Machine Learning is contributing to addressing fundamental application and operational issues such as security, handling large volumes of data, clustering, routing, and aggregation.

1. Healthcare
2. Industrial Use
3. IOT based edge computing with machine learning
4. Security in IoT Devices

Current approaches to allocating random access in the context of serving extensive machine-type communication applications often encounter issues such as congestion and excessive signalling overhead.
To address these challenges and meet the low latency and high reliability requirements of smart Internet of Things applications with strong control over Quality-of-Service constraints, the third-generation partnership project introduced the concept of fast uplink grant allocation, which addressed a robust and sufficient measure towards the challenges that came up while working through the application of machine learning.

4. APPLICATIONS OF MACHINE LEARNING IN IoT DEVICES

5.1 HEALTHCARE APPLICATION THROUGH ML IN IoT DEVICES

In IoT applications for the personal health and healthcare sector , selecting the most optimal machine learning (ML) methods depends on the specific use case, data characteristics, and desired outcomes.

Here are some ML methods that can contribute to optimising IoT applications in personal health

1. **Feature Extraction/Selection**
2. **Dimensionality Reduction**: Techniques such as Principal Component Analysis (PCA) can assist in reducing the dimensionality of data, particularly when dealing with a large number of sensor features.
3. **Signal Processing**: Before feeding sensor data into ML models, signal processing techniques can improve its quality.

4. **Random Forests**: A decision tree ensemble that can handle complex data interactions, improve generalisation, and provide insight into feature importance.
5. **Gradient Boosting**: Algorithms such as XGBoost and LightGBM can improve predictive accuracy by building strong models sequentially based on the weaknesses of previous ones.

Transfer learning uses pre-trained models from larger datasets (e.g ImageNet) to fine-tune them for personal health data, which is especially useful when labelled data is scarce.

Health Intervention: Using an individual's health data, reinforcement learning can help determine optimal interventions, such as adjusting medication dosages.

Long Short-Term Memory (LSTM) Networks: Because LSTM networks excel at capturing temporal dependencies in time series data, they are well suited for health monitoring and prediction.

GRUs (Gated Recurrent Units): GRUs, like LSTMs, are capable of detecting sequential patterns in data.

Isolation Forests: These algorithms can detect anomalies in data efficiently without requiring a large amount of training data.

Unsupervised models that can learn latent representations of data and are useful for detecting subtle anomalies are known as autoencoders.

Federated Education: In cases where data privacy is an issue, federated learning allows model training across distributed devices while keeping data locally.

Combining Rule-Based and Machine Learning Approaches: Integrating domain-specific rules with machine learning models can result in more accurate and interpretable results, particularly in medical diagnosis.

One-Shot Learning: Creating personalised models with limited data using techniques such as one-shot learning.

Online Learning: Constantly updating models with new data to ensure they remain relevant and accurate over time.

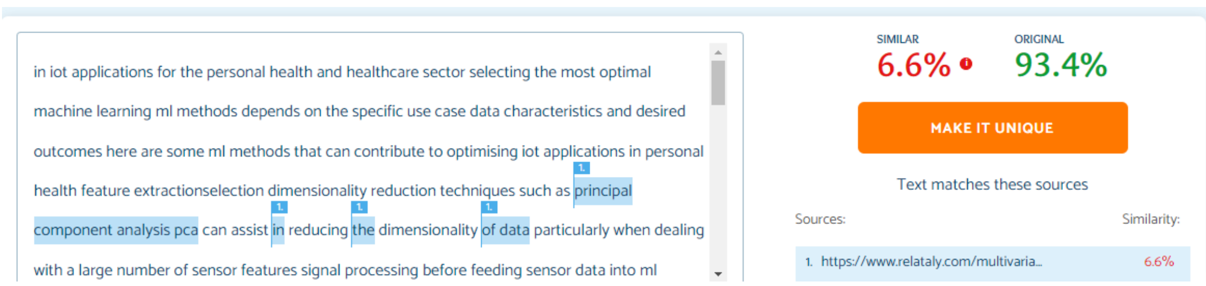
Attention Mechanisms: Attention-based models can highlight relevant features and aid in the explanation of model predictions, thereby increasing trust and understanding.

ML with Low Energy Consumption

Model Quantization: Converting models to lower precision (e.g. 8-bit) can significantly reduce computation requirements, which is critical for IoT devices with limited resources.

The best and optimal option is determined by factors such as available data, computational resources, latency requirements, interpretability requirements, and the specific goals of the personal health IoT application.

Experimenting with multiple methods, comparing their performance, and fine-tuning them to achieve the best results for the given context is frequently beneficial and gives out the comparison of the most precise outcome and prediction for the methods and applications used.



5.2 INDUSTRIAL USE IN IoT DEVICES THROUGH ML APPLICATIONS

Machine learning (ML) methods are critical in industrial IoT applications for optimising processes, predicting failures, increasing efficiency, and making knowledge based conclusions.

The ML methods used are determined by the specific use case and goals of the industrial application.

Here are some ML methods that are commonly used to improve the performance of industrial IoT applications:

Classification and Pattern Recognition: Based on sensor data, images, or other relevant features, ML models can classify products as defective or non-defective.

Convolutional Neural Networks (CNNs) can be used for visual inspection, detecting defects in products via images or video streams.

Forecasting Demand: To optimise inventory management and supply chain operations, time series analysis and machine learning algorithms can predict demand patterns.

Route Optimisation: Machine learning algorithms can be used to optimise delivery routes in order to reduce transportation costs and improve delivery times.

Prediction of Energy Consumption: ML models can predict energy consumption patterns in order to optimise energy consumption and reduce costs.

Anomaly Detection: Machine learning techniques can detect abnormal energy consumption patterns, which may indicate equipment malfunctions or inefficiencies.

Machine learning can detect dangerous conditions by detecting anomalies in sensor data related to temperature, pressure, or other safety-critical variables.

Natural Language Processing (NLP): NLP can be used to identify patterns and potential risks in incident reports and safety documentation.

Control System Optimisation: To maintain optimal process conditions, ML algorithms can optimise control parameters in real-time.

Model Predictive Control: This method optimises control inputs by using dynamic models and predictions to achieve desired process outcomes.

Sensor Fusion: Combining data from multiple sensors provides a comprehensive view of the industrial process, improving prediction and control decision accuracy and reliability.

Integrating domain-specific rules with ML models improves interpretability and ensures that decisions are consistent with expert knowledge. Experimentation, testing, and continuous monitoring are essential for validating ML model performance and making necessary adjustments.

5.3 IOT BASED EDGE COMPUTING WITH MACHINE LEARNING

Edge computing for IoT (Internet of Things) and machine learning is a potent strategy that involves processing and analysing data closer to the data source at the network's edge rather than transmitting all the data to a central cloud server for analysis.

This method has a number of advantages, such as decreased latency, enhanced privacy and security, and the capacity to make judgments in real time without relying on a continual internet connection. IoT edge computing and machine learning combine in the following way:

- **Data gathering**: IoT devices gather data from sensors, cameras, and other real-world sources. These gadgets might be anything from smart cameras at a store to temperature sensors in an industrial setting.
- **Preprocessing of Data**: IoT device raw data may include noise, outliers, or unnecessary information. The data can be preprocessed by edge devices by filtering, aggregating, or converting it into a format that is appropriate for analysis.
- Machine learning models are directly deployed and executed on edge devices or edge gateways. These models are capable of carrying out various tasks, including anomaly detection, predictive maintenance, and picture recognition.
- **Making decisions in real time**: Devices can make decisions in real time without sending data to a central server by executing machine learning models at the edge.
- Optimising bandwidth: Sending raw data to the cloud for processing can be expensive and bandwidth-intensive. Because only pertinent data or insights are transferred to the cloud when using edge computing, less data must be delivered.
- **Privacy and security**: By processing sensitive data locally and eliminating the need to transport it to remote servers, edge computing can improve data privacy. For applications requiring private or confidential information, this is especially crucial.
- **Scalability**: By simply adding more edge nodes or gateways, edge devices can be readily expanded, enabling distributed processing and enhanced system performance.
- **Adaptability**: Edge machine learning models don't need to constantly communicate with a central server in order to adjust to local conditions and environmental changes.

5.3.1 Workflow of Edge computing with ML:

Although the detailed execution and flow/process of different systems might vary slightly ,the general conceptual implementation of edge computing devices that integrate Machine Learning capabilities follow these general steps:

1. **Device Setup**: IoT devices, equipped with sensors and data collection capabilities, are deployed in the field. These devices can include sensors, cameras, industrial machinery, vehicles, wearable devices, and more.
2. **Data Collection**: The IoT devices gather data from their environment. This data could be in the form of images, sensor readings, audio recordings, location information, or any other relevant data type.
3. **Local Processing**: Instead of sending all the raw data to a centralised cloud server, the IoT devices perform local processing. This may involve initial data preprocessing steps such as noise reduction, data normalisation, and feature extraction.
4. **Edge Node**: In edge computing, an intermediate device called an edge node or gateway is often used to handle more sophisticated processing tasks. This could be a dedicated piece of hardware or a software component running on a local server.
5. **Machine Learning Deployment**: Deployment of ML models at edge nodes is done. The models are trained on previously aggregated data and implemented for various tasks like object and anomaly detection, regression, classification etc.
6. **Inference**: When new data is collected, the deployed machine learning model runs inference on this data. Inference involves applying the trained model to the input data to make predictions or classifications.
7. **Local Decision Making**: Based on the results of inference, the edge node can make local decisions in real-time. For instance, in a manufacturing setting, if an anomaly is detected in machinery, the edge node might trigger a maintenance alert or halt the machinery to prevent further damage.
8. **Data Filtering and Aggregation**: Since edge devices have limited computational resources and bandwidth, they can filter and aggregate data before sending it to the cloud. This reduces the amount of data transmitted and focuses on sending relevant insights
9. **Intermittent Connectivity**: Edge devices might experience intermittent or limited connectivity to the central cloud server. By processing data locally, these devices can continue to function even during network outages, ensuring critical tasks are not disrupted.
10. **Cloud Integration (Optional):** In some cases, selected data or insights are sent to the cloud for further analysis, long-term storage, and complex processing. This allows for a combination of local decision-making and more extensive cloud-based analytics.
11. **Model Updates**: Edge machine learning models can be periodically updated to improve accuracy or adapt to changing conditions. These updates can be done remotely, ensuring the latest models are always in use.
12. **Security and Privacy:** Processing data at the edge enhances security and privacy by reducing the amount of sensitive information sent to external servers. Only relevant insights or anomalies are shared.
13. **Scalability:** As the deployment scales, more edge devices or nodes can be added to distribute the computational load and handle increased data volume.

    Overall, edge computing with machine learning enables real-time, localised decision-making by processing data closer to its source. This approach improves responsiveness, reduces network congestion, and enhances the overall efficiency of IoT systems. It's particularly valuable in applications that require low latency, efficient use of resources, and robust operation in challenging network conditions.

5.3.2 Techniques/Algorithms used to apply Machine Learning to Edge Computing

Unlike other conventional modern algorithms that are used cannot be implemented in the same manner in edge computing due to limitations in processing power, memory limitations without affecting performance. Therefore the models are modified in such a manner as to make them viable for deployment in edge computing devices.

- K-NN model with Compression techniques: Various compression techniques like ProtoNN are used to train models on edge devices. As such devices contain low memory and storage capabilities and implementation of standard KNN needs the entire dataset to be stored, compression techniques are used to convert data to lower dimensional space and selecting a few samples that are used for accurate prediction.
- Support Vector Machines: SVM are used in classification and regression problems and are proven to be highly compatible for task with relatively less data.
- Decision Trees: It is effective for classification and regression models. They are frequently used in edge computing since they are known to be less computational resources intensive in comparison to other algorithms.