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Frameworks for Industrial Internet of Things by Using Open Source Machine Learning Techniques

Dr. Mahesh kotha[1], Dr. J. Srikanth[2], Sathini Santhosh Kumar3

Associate professor, Department of CSE (AI&ML), CMR Technical Campus, Hyderabad[1]

Associate professor, Department of CSE, Kommuri Pratap Reddy Institute of Technology, Hyderabad[2]

Assistant Professor, Dept of CSE, Vigna's Institute of Management and Technology for Women, Hyderabad[3]

Abstract: The Internet of Things (IoT) has acquired notoriety also, is progressively utilized in huge scope arrangements for modern applications. Such deployments depend on the adaptability and versatility of frameworks and gadgets. Heterogeneous frameworks should be interoperable also, cooperate flawlessly. To oversee such arrangement of frameworks, it is significant to work with a structure that not just backings the adaptable idea of IoT frameworks yet in addition gives satisfactory help for modern prerequisites, like constant also, runtime highlights, building draws near, equipment requirements, normalization, modern help, interoperability, and security. The choice of a fitting system results troublesome because of the rising number of accessible structures and stages, which offer different help for the previously mentioned necessities. Thusly, this article researches the highlights of seven conspicuous structures to improve on the determination of a reasonable structure for a modern application. The point of this article is to introduce the new turns of events and best in class of modern IoT structures and give a specialized correlation of their elements and attributes. The study investigates the open source machine learning frameworks, aligned with the industrial domain (processing data generated from Industrial Internet of Things), in terms of usage, programming languages, implementations, and future prospectus.

Key word: Frameworks, Industrial Internet of Things (IIoT), system of systems (SoS), Cloud services.

I. INTRODUCTION

Machine learning applications are quickly transforming the industrial landscape. Many businesses have reduced the production and operation costs using tools powered by machine learning models and algorithms. The deep learning which is a subset of machine learning has found ways in manufacturing, industrial maintenance, drug discovery, pattern imaging analytics, and software testing [1]. The deep learning a type of deep neural network consisting of layered structure as input layer, hidden layer, and output layer. Industrial Internet of Things (IIoT) is defined as a set of machines, robotics, cognitive technologies, and computers for intelligent industrial operations with the help of data analytics [2]. The Industrial Internet of Things is a part of Industry 4.0 revolution, which is concerned with automation, innovation, big data, and cyber physical systems in industries. The Industrial Internet of Things are showing positive impact in supply chain, transportation, healthcare, manufacturing, oil and gas, energy/utilities, chemical, and aviation industry. The Industrial Internet of Things has helped in controlling and monitoring manufacturing and production from remote locations [3]. The Industrial Internet of Things market will reach $123.89 Billion by 2021 [6]. Industrial Internet of Things captures large chunk of data, later used for predictive maintenance, time management, and cost control after machine learning models implementation. The machine learning models forms the core of logistics and supply chain solutions in terms of optimizing the product packet size, delivery vehicle selection, delivery route selection, delivery time computation. For instance DHL uses Amazon's Kiva robotics (improve speed, accuracy) for the network management.

The Industrial Internet of Things and machine learning models are inseparable entities for optimal solutions as far as the industrial context is concerned. However, the machine learning models need development, training, and testing in a software/ programming framework before being put in actual use. These software/ programming frameworks (IBM Watson) are often termed as software development environment/ model development environment, have licensed fee. The licensed fee prevents small industries in experimenting the machine learning models for their own need. Therefore, the study illustrates the open source machine learning frameworks (TensorFlow, Torch, etc.) for designing machine learning model using data generated through Industrial Internet of Things. Even small size industries can experiment with machine learning models for business forecasting and resource management.

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The objectives of this survey are as follows.

- To provide a picture of the current state of the art of IIoT frameworks. The framework features and group alliances are continuously evolving and expanding, and consequently, published surveys rapidly become obsolete. The information provided in this article is updated and accurate at the time of writing and uses original specifications and documents from the included groups and projects.

- To provide a high-level comparison of the most prominent frameworks in the industrial and automation domain that are supported by important research groups and company alliances.

- To illustrate a comparison and analysis of IIoT frameworks in terms of fulfilling industrial IoT requirements, such as interoperability, security, adaptability, and standardization as well as community and industrial support.

This article presents a technical comparison of IoT frameworks engaged in the current industrial context that provide SoS solutions to Industry 4.0 issues. This article provides a detailed summary of the functionalities, domains, and technological features of cutting edge frameworks and a brief overview of cloud-based platforms launched by major IoT shareholders. The information presented has been gathered from official repositories and sources. The analysis criteria include key automation and digitization requirements, such as real-time and runtime features, hardware requirements, architectural approaches, entry barriers, industrial support, standardization, interoperability, and security.

II. RESEARCH BACKGROUND AND MOTIVATION

According to one estimate, the number of Industrial Internet of Things devices will increase to 75.44 billion by 2025. The technologies enabling Industrial Internet of Things are: Internet of Things, artificial intelligence, cloud computing, artificial intelligence for Cyber Physical Systems (CPS), big data analytics, blockchain, augmented and virtual reality[7]. The key elements of Industrial Internet of Things are the smart devices, communication network, and big data analytics, Figure 1 shows the key elements of Industrial Internet of Things.

In the following section, emerging frameworks for IIoT are presented. In this context, an IIoT framework is considered a set of principles and characteristics that enable IIoT application. The frameworks are presented in alphabetical order and were not ranked in any way.

The following frameworks have been selected based on the following criteria.

i) The industrial character and focus on the Industry 4.0 objectives.
ii) The provisioning of architectural and technical solutions for industrial contexts beyond individual IoT solutions.
iii) The targeting of SoS applications based on the IoT.
iv) The reputation of the consortia members and support from large projects.
v) Their future potential and emergence.
vi) The marked evolution from the cloud to the edge.

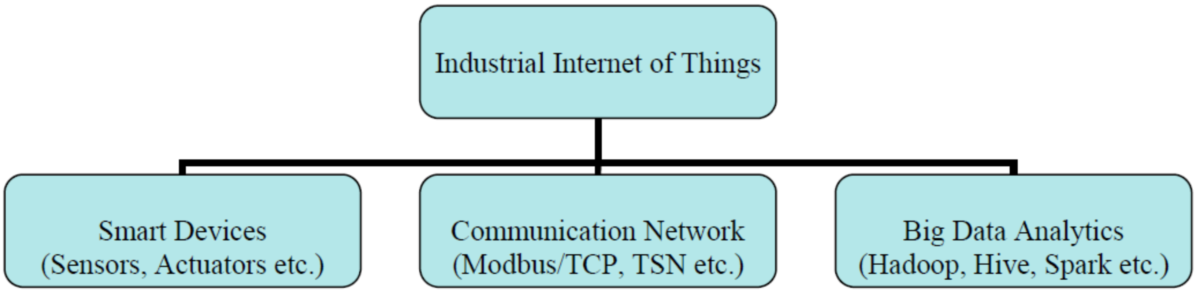

Fig 1. Key Elements of Industrial Internet of Things

The machine learning is a subset of artificial intelligence. The machine learning is of various types such as supervised (input and output features are known in advance), unsupervised learning (algorithm/ model learns dataset patterns and group them into clusters), and reinforcement learning (learning takes place because of reward and punishments). The image classification, fraud detection, disease diagnosis, weather, and market forecasting uses supervised learning (Linear

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Regression, Support Vector Machine, Decision Tree, K Nearest Neighbor). The recommender system and big data visualization uses unsupervised learning (K-Mean Clustering, FP Growth). The real time decision and robot navigation uses reinforcement learning. The machine learning technologies in the form of mobile intelligences and Automated Guided Vehicles (AGVs), are used within industries to improve productivity, efficiency and reliability [8]. The Industrial Internet of Things applications in industries requires standards and intelligence techniques such as low-power wireless networking technologies and fast sensors for big data analytics [10]. The data collected during industrial production and operation by the sensors are stored over cloud for analysis and prediction [10]. The machine learning algorithms are used in the feature selection of Industrial Internet of Things [12].

III. IIoT ARCHITECTURE

The IIoT architecture, as described in the IIoT framework, is an integrated set of the components needed for the success of IIoT Without the architecture, consisting of hardware, software, security and communications, there would be no means to gain the benefits of the IIoT. Figure 2 was constructed from the architecture within the literature as described by Pena et al. [13], Boyes et al. [14] and Holdowsky et al. [15] These views were taken into account together with the responses from the interviewees in constructing the needed architecture as depicted in Fig. 2. The constructed IIoT. Architecture did not take into account the suggestions of the addition of a data validation layer as described by the works of Kristofferson et al. [16]. This additional view could complement the proposed IIoT Architecture in Fig. 2.

In Fig. 2, the data generation layer contains the measuring devices, also called things in the IIoT domain, that measure different parameters. These devices consist of hardware and software components. There could be machine-to-machine communication within the device level, and the various communication protocols are of relevance. Automation could also be within this level of IIoT. Security on this level is necessary to ensure data integrity and to prevent stoppages in the production environment. Measuring devices could communicate wirelessly with the data collect and store layer, and a high level of robustness is needed for the continuous functioning of the hardware. Data flow from this lower level to the data collect and store layer. The data collect and store layer identified from the findings also consists of a hardware and software component. The hardware could be locally on the premises or make use of off-site cloud services. The hardware is used in conjunction with software to collect and store data. There is also a high level of security needed in this layer. The data could consist of structured or unstructured data and could utilise big-data sources. Lastly, the data contextualize layer – be it on-site, off-site or in the cloud –presents the data in a way that the business could make sense of the data. Data become information within this layer and could be visually presented in the form of a report or a Supervisory Control and Data Acquisition (SCADA) display. Analytics could also be done within this layer as well as machine learning and pattern recognition. Conboy et al. [7] mention value-generating mechanisms. These mechanisms, in regards to analytics, could complement the data contextualization layer in the proposed IIoT architecture.

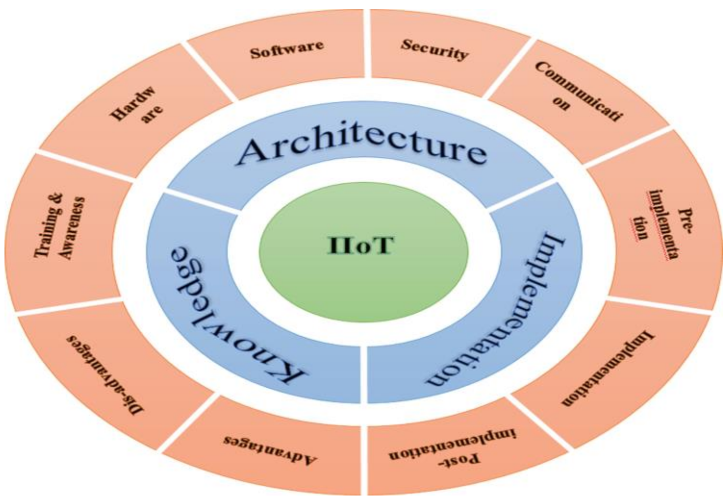

Fig. 2. IIoT framework

Hardware. A critical consideration in the selection of the equipment in an industrial environment is hardware that can withstand the harsh production conditions. In a mining environment, the environmental factors in the mining area could be extreme heat, dust, mechanical forces and rain. For any hardware to keep functioning, it must be able to withstand these elements. It is also crucial for the device to maintain operation within an industrial environment. If the hardware

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were to fail, it could mean safety incidents or production losses. Equipment should be highly reliable, robust, possess a high resilience to failure and be available whenever the process needs their functioning. In certain areas, hardware redundancy is in place to ensure that hardware in a particular process is backed up with a set of standby equipment in case of failure. The following minimum hardware needs to be in place for any IIoT implementation to be successful:

IIoT devices.

• Considering the scalability of IIoT devices when they grow into the thousands was also cited as a consideration before the application of the IIoT hardware devices. The respondees mentioned that the questions during an implementation consideration:

Would there be enough technical resources to install the magnitude of sensors required in installation going into the thousands of sensors? Also, is the supporting hardware that hosts the platforms able to process the amount of data?

• Networks and network coverage for the communication between the different layers.

• A hardware platform host could be in the cloud or on-premise. This hardware platform hosts the data storage, collection and contextualisation of the data. From the findings, it should be noted that if no reliable connectivity to the cloud is available, the storage, collection and contextualisation of the data needs to be handled on-site. This is in order not to expose the business to risk if there are communication interruptions to the cloud that could affect a critical process. An example could be when a manufacturing process that moulds plastic loses connectivity to the cloud and the process halts. Consideration should be given if there is enough hardware space allocated for the storage of the information and the hosting of the services.

• Gateway devices that aid security solutions.

Software: The software platforms needed for the IIoT solution and whether these platforms could easily integrate with existing platforms should be considered. In this regard, Karschnia [3] mentions that these “things” interconnect on- and off-site to software platforms to enable remote control, monitoring and asset management using either dedicated expert teams or specialised data analysis software connected to big data lakes to add value.,

Interviewees indicated their experience with prior implementations is that it is essential to do a consolidation of different source data before any implementation takes place. Within the IIoT, intelligence could move down to the instrument level. If this is the case, intelligence will be needed at the measuring device level and the ability to handle automation on the lower level. The industrial systems should be easily and frequently reprogrammable to support changing processes. Within complex industrial processes, process improvements are regularly attempted. The systems that support these processes, therefore, need to be easily adaptable.

IV. OPEN SOURCE ML FRAMEWORKS AND IMPLEMENTATION PROCESS

The design, development, training, and testing of a machine learning model depends on the choice of machine learning frameworks. There are numbers of machine learning frameworks for developing the machine learning models. The open source frameworks for the machine learning model development in an industrial environment is shown in Figure 3.

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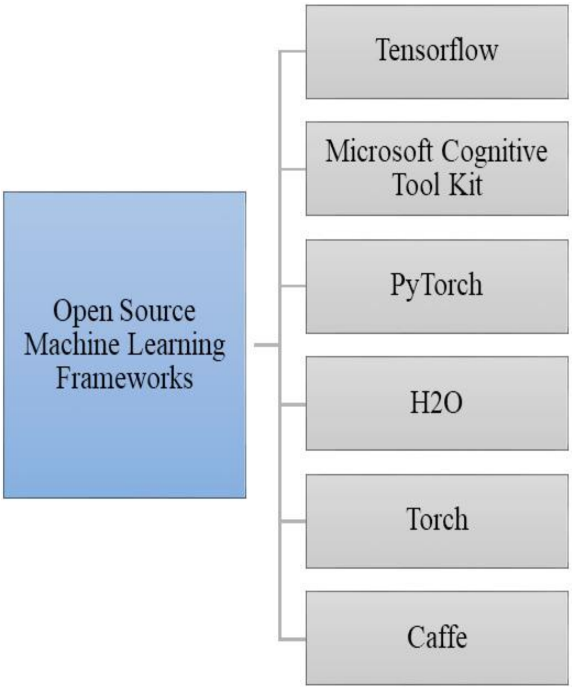

Fig 3. Machine Learning Frameworks for Industrial Internet of Things

IIoT Implementation

Pre-implementation. Before implementation of any IIoT solution, there must be a need or a problem to be solved. A clear understanding of the business/user requirements and information is imperative. The business need should be supported by a clear business case that justifies the implementation of the technology and ensures that there is a return on the investment in the technology. This business requirement should be documented to ensure that the IIoT solution would support the need.A detailed design document, based on the user requirements, should then be created before any IIoT implementation. This intricate design could direct the implementation of the IIoT solution. This design needs to consider the key performance indicators that need to be achieved as well as the available technology. The detailed design should also determine if the implementation is a new (greenfields) installation or an existing (brownfields) installation. It should be determined if the existing infrastructure and architecture are compatible with the existing infrastructure. A decision on the technology should be made. This selection of technology would need to consider the ease of serviceability and maintainability of the technology and paths should be upgraded during the life cycle. The business should have a clear vision of how the realization would function after the implementation, and what the expectation is from the application. In terms of personnel, planning should take place for skilled staff after the installation to maintain the IIoT implementation. Consideration should be given regarding whether the solution implementation is a success. If the advantages of the IIoT implementation realise with an increase in production, would the additional product produced from a successful IIoT implementation be sellable and is there a market for it? Can the organisation's logistics accommodate the increase in the product?

Blanchette [9] emphasised the importance of thorough planning before any IIoT implementation commences. Planning was also cited as an essential factor before any IIoT rollouts could begin as there is no identification of formal IIoT guidelines. Lueth [3] in this regard states that IIoT projects take over 18 months longer than what had initially been planned. At the base of thorough planning, Blanchette [9] iterates the creation of a baseline (as-is) situation of the organisation. The responders mentioned that the baseline should consider:

• If there are cloud services used, the presence of data analytics, the relevant needed reports for decisions and the level of automation.
• The business demographics.
• Scalability of IIoT devices when they grow into the thousands.
• Compatibility of newer equipment and systems within IIoT to function with existing or legacy systems.
• The consolidation of different source data, before implementation.
• A clear vision of where the business wants to position themselves in the future.

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• A clear understanding of the needed technology to be implemented.
• Data flow mapping of where the data originates from to where it is needed.

Detailed architecture is necessary when the implementation of IIoT solutions commences and needs to contain decisions on the selected technology. Change management during execution is critical to ensure that the solution is adopted and the benefits are realised. During the execution of the IIoT implementation, it is vital to use a skilled implementations team. Recommendations during the implementation of IIoT solutions from the respondents were that small achievable project milestones should be planned and pursued to ensure the IIoT implementation success. The time needed for a large scale IIoT implementation should be kept in mind.

Tensorflow: The Google owns Tensorflow. It is used in deep learning (deep learning is a subset of machine learning). The Tensorflow has many versions but the latest versions are faster, more flexible, and support new languages. It is used by multinational companies such as Qualcomm (for snapdragon mobile platforms), Intel (for Intel platform), China mobile (for detecting network anomalies'), and CEVA (deep learning processors). Tensorflow supports high performance computation for face and handwriting recognition. It run on Graphical Processing Unit (GPU), CPU, servers, desktops, and mobile devices. The C++/ Python graphs from Tensorflow is used for
processing on CPUs or GPUs.

Microsoft Cognitive Toolkit: The Microsoft owns the Microsoft Cognitive Toolkit. It helps businesses and organizations in exploring the machine learning solutions. It is an open source deep learning development environment and supports multi-machine-multi-GPU-back-ends. Initially, it was designed to learn on the pattern of human brain, now it can be used for feed-forward Deep Neural Network (DNN), Recurrent Neural Networks (RNN), and Convolution Neural Networks (CNN). Its usage include predictive maintenance solutions of aircrafts. In September 2017, Microsoft released Azure Machine Learning Model Management tool to help developers in management and deployment of machine learning workflows.

H2O: It is the one of the biggest open source machine learning model development framework for business and enterprises. The HORTIFRUT industry optimizes the processing of blue berries using H2O. The Stanley Black and Decker optimizes the manufacturing processes and reduces the time and costs. The Intel uses it for network traffic and intrusion detection.

Torch: The Torch is an open source machine learning model development framework. The Facebook owns it. The Torch is a library, scientific computing framework, and script language for machine learning based on GPU/CPU. Torch is flexible and easy to use. It is used by companies such as Purdue, Yandex, and NVIDIA.

PyTorch: The Facebook owns PyTorch. It is similar to Torch and less matured than Tensorflow. The PyTorch follows an object-oriented paradigm. The code writing in PyTorch is easy due to conditionals and loops functionality. The PyTorch is used by companies such as IBM, Facebook, and Yandex.

Caffe (Convolutional Architecture for Fast Feature Embedding): It was developed at Berkeley Vision and Learning Center (BVLC). It is one of the fastest systems for DNN and can process 60M images/day with a single GPU. Caffe offers easy configuration and switching between GPU and CPU for model training. The companies such as Google and Pinterest uses Caffe for computer vision, speech, and multimedia content analysis. The Caffe, is used to build Convolutional Neural Network (CNN) for image classification.

Machine learning based systems in manufacturing sector solves the supply chain and predictive maintenance problems. The Airbus has a dedicated unit for identifying gaps in the manufacturing process by using sensors, tools, and wearable technologies. Figure 3 shows the machine learning frameworks implementation process in industrial setting.

The industries like assembling, oil and gas, and store network produces information through sensors, actuators, and versatile applications. These information are put away either at nearby server/at cloud for additional handling. In the wake of cleaning the information, the machine learning systems, for example, Tensorflow, Light and so on, chose for applying different machine learning models (Direct Relapse, Backing Vector Machine, Choice Tree, and so on) on the given datasets.

The model creating the most noteworthy score in the disarray network for a given informational index is acknowledged and it is utilized for expectation on another informational collection. The leaders utilizes the AI model results in dynamic cycle.

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V. RESULTS AND DISCUSSION

The machine learning models give answers for industry explicit issues as income age, client conduct examination, creation process mechanization, and cost advancement other than expectation and determining. The machine learning models help in peculiarity discovery (steel fabricating plants), quality appraisal (auto industry), and stock administration in assembling ventures. The Modern Web of Things (sensors, actuators, web applications, and the executives frameworks) produces immense volume and assortment of information. The volume and assortment are enormous information qualities [4]. In the principal case, the information is utilized for creating, preparing and testing of an machine learning model. The machine learning calculations (grouping (Arbitrary Backwoods, Backing Vector Machines), bunching (K-Means, K-Closest Neighbors), and paired order (Strategic Relapse)) which fits best with the information frames the foundation of the machine learning model. The machine learning systems help in the advancement of machine learning model. Table 1 shows the open source machine learning systems.

Table 1. Comparison of Open Source Machine Learning Model Development Environment

Machine Learning Frameworks	Supporting Language	Supporting Platform	Maintainer	Applicability
Tensorflow	Python and C++	Windows, MacOS and Linux	Google	Deep speech, smart reply, and computer vision.
Microsoft Cognitive Toolkit	Python, C++, and C#	Windows and Linux	Microsoft Research	Handwriting, image, and voice recognitions
Caffe	C, C++, Python, and MATLAB	Ubuntu, MacOS, and Windows	BVLC	Training models for classification.
H2O	Java and Python	Windows and Linux	H2O	Creates productionize machine learning models.
Torch	Lua	Linux, Android, MacOS, iOS and Windows	Ronan, Clément, Koray and Soumith	Detecting and solving hardware problems for data flows.
PyTorch	Python	Linux, Android, MacOS, iOS, and Windows.	Ronan, Clément, Koray and Soumith	Reinforcement learning and scaled production of models.

Although, the manufacturing and transportation organizations are burning through great many dollars on Modern Web of Things and its administrations, few out of every odd industry with Modern Web of Things has had the option to take advantage of the created information and machine learning applications. It is critical to pick the machine learning structures taking into account interoperability with Modern Internet of Things information. Figure 4 shows the machine learning systems and the patterns on Google during most recent one year.

Among the accessible open source machine learning systems, the Tensorflow has the biggest local area and client base. The PyTorch has the second biggest local area. The Microsoft Mental Toolbox, Caffe, and H2O have extremely low perceivability among the clients. The Tensorflow and PyTorch are on the top among the five system, as they support every one of the working frameworks with documentation. Among different things these two structures support discourse acknowledgment and PC vision (object location, object acknowledgment, object characterization, object division).
The discourse acknowledgment and PC vision is the most sweltering subject of conversation and examination in modern conditions.

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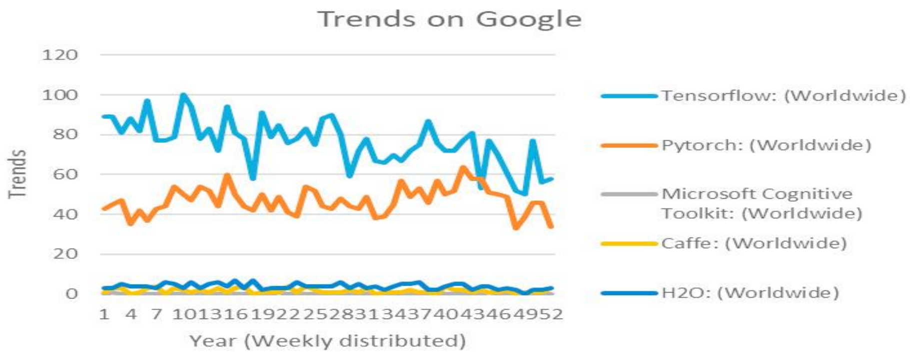

Fig 4. ML Frameworks and Google Trends during last year (2020)

Challenges

Personnel with the appropriate experience in delivering IIoT solutions in the specific industry is needed for the implementation and maintenance of implemented solutions. Other challenges include:

• Management of cultural and organisational changes.
• Business representatives are reluctant to support the implemented solutions if the proper change management did not occur before the IIoT implementation.
• New technology introductions into the existing infrastructure and environment in terms of the connectivity, security and platforms.
• Existing infrastructure and platforms exist when implementing IIoT.
• Greenfields organisations have no challenges in terms of legacy systems.
• People skills in terms of IIoT.
• Existing communication protocols in use.
• Existing systems and hardware that are in use.
• Network connectivity challenges.

VI. CONCLUSION

This paper introduced a found structure for the IIoT that could be utilized as a premise for IIoT execution explicit choices. This structure would help mining agents in executions of IIoT arrangements. In 2017, just 12% of mining agents had carried out IIoT answers for a degree or a full degree [8]. The World Financial Gathering [9] predicts that the normal effect of computerized change on the mining industry is in the area of US$428 billion and US$ 784 billion. This structure incorporated the required IIoT design while considering the explicit equipment, programming, security and correspondence viewpoints. Inside this system, there was likewise a thought as far as pre-, during and post-execution viewpoints and investigated the benefits, burdens and preparing concerning the IIoT. The utilization of this system would help modern associations and partners in terms of IIoT answers for comprehend the particular contemplations in regards to the IIoT.

Machine learning are shaping the future industries. The machine learning can possibly advance the enterprises and their plans of action. The machine learning execution on Modern Web of Things information has enormous advantages to enterprises like shopper request expectation in energy businesses, production network changes, prescient support, quality control, and increment creation throughput.

Notwithstanding, new participants face hardships to comprehend and utilize the accessible machine learning structures for information handling and machine learning model turn of events. Exploring the accessible open source is significant machine learning systems for receiving the rewards. The review has introduced five open source systems for machine learning model turn of events. The concentrate further shows the information age in Modern IoT climate and the machine learning structure execution process. The future work would carry out Tensorflow on Modern Web of Things information from oil and gas industry to foster a prescient upkeep model in view of machine learning and deep learning.

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