Securing Smart Sensing Production System Using ML & DL Algorithms

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ABSTRACT—Industry 4.0 is the new industrial revolution. By connecting every machine and activity through network sensorstotheInternet,a hugeamountofdata is generated. Machine Learning (ML) and Deep Learning (DL) are two subsetsof Artificial Intelligence (AI), which are usedto evaluate the generated data and produce valuable information aboutthe manufacturing enterprise, while introducing in parallel the Industrial AI (IAI). In this paper, the principles of theIndustry 4.0 are highlighted, by giving emphasis to the features, requirements, and challenges behind Industry 4.0. Inaddition, a new architecture for AIA is presented. Furthermore, the most important ML andDL algorithms used inIndustry 4.0 are presented and compiled in detail. Each algorithm is discussed and evaluated interms of its features,its applications, and its efficiency.Then,wefocusononeofthe most important Industry 4.0 fields, namely the smartgrid, whereML and DLmodels are presented and analyzed in terms ofefficiency and effectiveness in smart gridapplications. Lastly, trends and challenges in the field of data analysis in the context of the new Industrial era arehighlighted and discussed such as scalability, cybersecurity, and big data.

Index terms— Machine Learning and Deep Learning, Artificial Intelligence.

I. INTRODUCTION

The large amount of data produced daily on theplanetandtheriseofrecentexponentially growing technologies (e.g. IoT, Big Data, cloud computing) in combination with the need for faster and better production ofproducts and services, have created a new trendinindustry,theIndustry4.0.Industry 4.0combinesseveraltechnologies.CPS,IoT, cloud computing and Big Dataanalytics are used to automate the production process,optimize products, reduce cost, reduce energy waste andprovide useful information by analyzing the data collected from different aspects across the manufacturingenterprise, including manufacturing equipment, manufacturing process, labour activity, and environmentalconditions. In general, Industry 4.0 optimizes the computerization of Industry 3.0. Once computers were introduced in Industry 3.0, due to the addition of a completely new technology, it was disruptive. Today, andas Industry 4.0 progresses in the future, machines arelinked and collaborating with each other to make decisions without human involvement in the end (1),(2).

It can be easily spoken that Industry 4.0 is drivenbyfourfundamentalaspects.First, are the digitization ofproduct and service offerings? The integration of newdata collection and analysis methods, such as the expansion of existing products or the creation of new digitized products, helps companies to generate product usage data and, therefore, to refine products in order tobest meet the needs of customers. Second, it is the digitization and integration of verticalandhorizontalvaluechain.Industry

4.0 incorporates processes throughoutthe enterprise, such as processes in product development, production, distribution and service, while Industry 4.0 vertically covers internal operations from manufacturers to consumers and all key value chain partners. Third is the digital business models and customeraccess. Customer satisfaction is a multi-stage, neverending process that needs to be changed at the momentas the needs of consumers change all the time. Companies therefore expand their offerings by setting updisruptive digital business models to provide their customers with digitalsolutions that best suit their needs(2; 3).By implementingtheIoTtechnologyinindustry toobtain data from the manufacturing enterprise, a hugeamount of data is generated. Nowadays, it is easierto handle and process this amount of data due to thegrowthofcomputationalpowerandcloud computing.ML and DL make use of the data collected by sensorsand actuators of the product line. In this way, the application of ML and DL help to reduce costs of themanual inspection personnel for defects on products andalso help to reduce the cost in the total value of theproduction. By extracting knowledge from aggregateddata, ML or DL techniques play a key role in identifyingstandardsandpatterns, producing valuable information about the state of the manufacturing equipmentmanufacturing process and introducing the principles ofAI in the industrial sector, forming this way the Industrial AI.

II. LITERATURESURVEY

The internet of things in manufacturing: Key issues and potential applications

With the globalization of the world's economy, manufacturing enterprisesare facing severe competition from their worldwide counterparts in terms of product price, function, quality, cost, and lead time. Theyarealsoexperiencinggrowingpressure to meet higher environmental standards due to enhanced producer responsibility [1]. Meanwhile, consumers have more diversified and demanding needs, e.g., customized products. These challenges have pushed the manufacturing industry to embrace new technologies to remain competitive and meet user demands. The Internet of Things (IoT), which has great potential in transforming the manufacturing sector[2],hasattractedtremendousattention from both academia and industry. Industrial internet: A survey on the enabling technologies, applications, and challenges

This project provides an overview of the Industrial Internet with the emphasis on the architecture, enabling technologies, applications, and existing challenges. The Industrial Internetis enabledbyrecentrising sensing, communication, cloud computing, and big data analytic technologies, and has been receiving much attention in the industrial section due to its potential for smarter and more efficient industrial productions. With the merge of intelligent devices, intelligent systems, and intelligent decisioning with the latest information technologies, the Industrial Internet will enhance the productivity, reduce cost and wastes through the entire industrial economy. This paper starts by investigating the brief history of the Industrial Internet. We then present the 5C architecture that is widely adopted to characterize the Industrial Internet systems. Then, we investigate the enabling technologies of each layer that cover from industrial networking, industrial intelligent sensing, cloud computing, big data, smart control, and security management. This provides the foundations for those who are interested inunderstandingtheessenceandkeyenablers of the Industrial Internet. Moreover,we discuss the application domains that are gradually transformed by the Industrial Internet technologies, including energy, health care, manufacturing, public section, and transportation. Finally, we present the current technological challenges in developing Industrial Internet systems to illustrate open research questions that need to be addressed to fully realize the potential of future Industrial Internet systems.

Manufacturing analytics and industrial internet of things

Over the last two decades, manufacturing across the globe has evolved to be more intelligent and data driven. In the age of industrial Internet of Things, a smart production unit can be perceived as a large connected industrial system of materials, parts, machines, tools, inventory, and logistics that can relay data and communicate with each other. While, traditionally, the focus has been on machine health and predictive maintenance, the manufacturing industry has also started focusing on analyzing data from the entire production line. These applications bring a new set of analytics challenges. Unlike traditional data mining analysis, which consistsofleandatasets(thatis,datasets with few features), manufacturing has fat datasets. In addition, previous approaches to manufacturing analytics restricted themselves to small time periods of data.The latest advances in big data analytics allows researchers to do a deep dive into years of data. Bosch collects and utilizes all available information about its products to increase its understanding of complex linear and nonlinear relationships between parts, machines, and assembly lines. This helps in use cases such as the discovery of the root cause of internal defects. This article presents a case study and provides detail about challenges and approaches in data extraction, modeling, and visualization.

III. PROPOSEDSYSTEM

The overview of our proposed system is shown in the below figure.

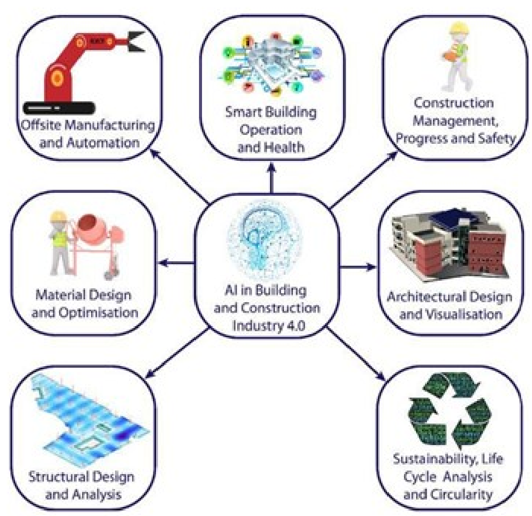

Fig.1:System Overview

ImplementationModules

- Upload SWAT WaterDataset: usingthis module we will upload dataset to application and then read dataset and then find different attacks found in dataset
- Preprocess Dataset: using this modulewe will replace all missing values with 0 and then apply MIN-MAX scaling algorithm to normalized features values and then split dataset into train and test where application used 80% dataset for training and 20% for testing

- Run Auto Encoder Algorithm: using this module we will trained Auto Encoder deep learning algorithm and then extract features from that model.

- Run Decision Tree with PCA: extracted features from Auto Encoder will get transform using PCA to reduce features size and then retrain with Decision tree. Decision tree will predict label for each record based on dataset signatures

- Run DNN Algorithm: predicted decision tree label will further train with DNN (deep neural network) algorithm todetect and attribute attacks

- Detection & Attribute Attack Type:usingthismodulewewillupload unknown or un-label TEST DATAand then DNN will predict attack type

- Comparison Graph: using this modulewe will plot comparison graph between all algorithms

ComparisonTable:usingthismodulewe will display comparison table of all algorithms which contains metrics like accuracy, precision, recall and FSCORE

IV. RESULTS

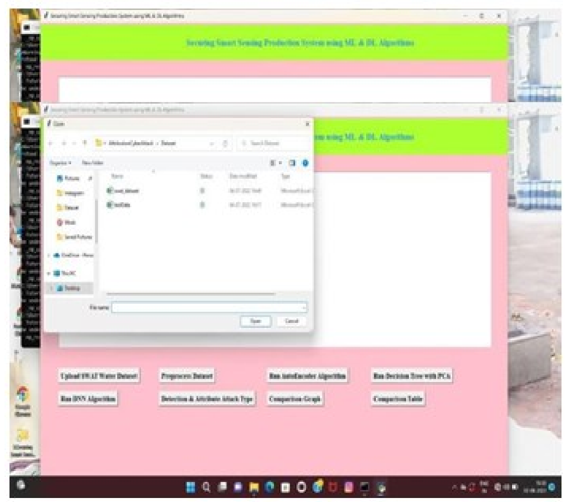

Fig.2:Openingpage

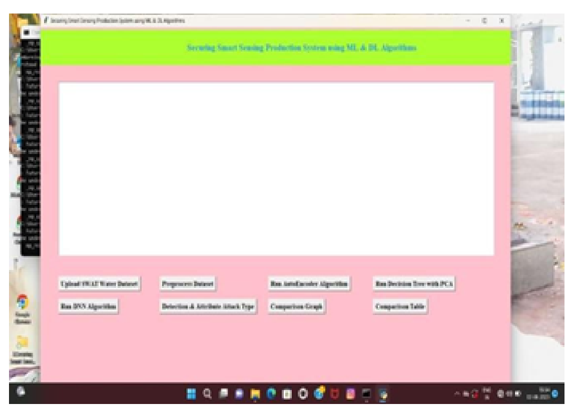

Fig.3:Upload Dataset

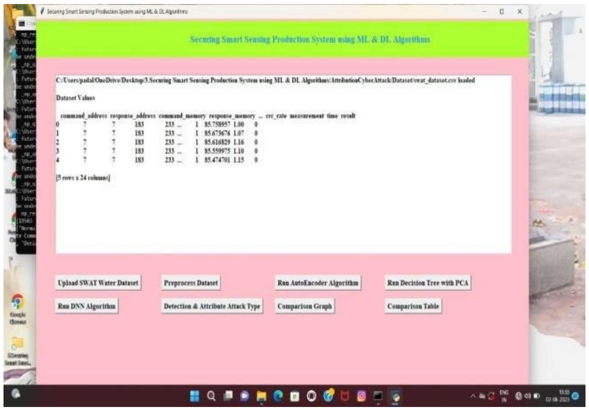

Fig.4:Preprocess

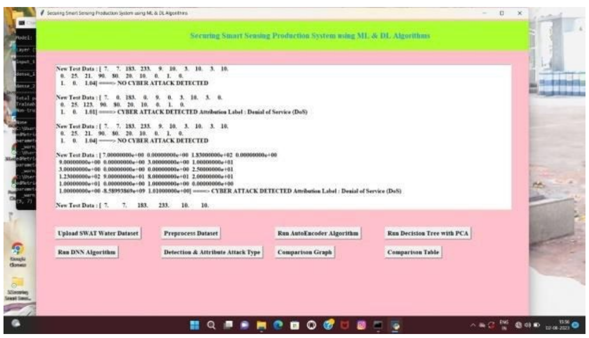

Fig.5:PredictedResults

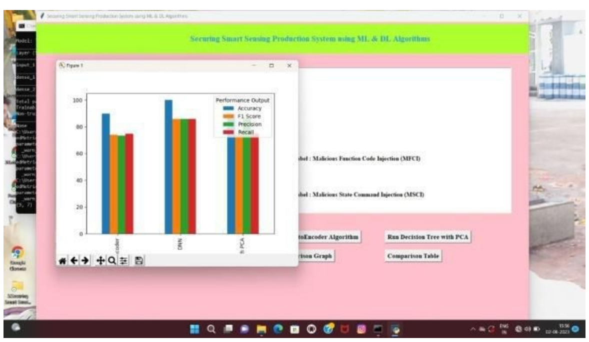

Fig.6:ComparisonGraph.

V. CONCLUSION

In this project, the new industrial revolution and thekey role of the Artificial Intelligence are surveyed anddiscussed. Initially, the fundamental elements and theEcosystem of theIndustrialAIareanalysedanda newapplication scheme of the Industrial AI is proposed.Furthermore, the ML and DL algorithms and modelsused inmanufacturing are discussed and presented thoroughly. An analysis of the ML and DL modelsandalgorithmsontheSmartGrid,an important field of Industry 4.0, is also implementedintermsof itsefficiencyandits applications. In conclusion, the challenges andtrends on the Industrial AI are also documented. The authors are of the opinion that Industry 4.0 has not fully incorporated Artificial intelligence into its operations andthere is still much to be done. Cybersecurity is an areathat needs special attention due to the interconnection ofthe manufacturing components to the internet. SPEARand SDN-microSENSE projects are working to provideoverall solutions in this field.As future work, the authors aim to apply and examinethe capabilities and the accuracy of the aforementionedmodels and algorithms in the use cases of theSPEARand SDN-microSENSE project. In particular,themodelsandalgorithmswillbe utilized for anomaly detection, RUL estimation and cost prediction.

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