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Towards Industrial Revolution 5.0 and Explainable Artificial Intelligence: Challenges and Opportunities

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Abstract: Technological growth is changing our everyday living, making it smarter and more convenient day by day; Smart society 5.0, Healthcare 5.0, Agriculture 5.0 are only a few examples indicative of our fast-evolving lifestyle. The Industrial Revolution 5.0 (IR 5.0) encapsulates future industry development trends to achieve prosperity beyond jobs by incorporating more intelligence in our everyday living with the help of cutting-edge technologies such as Explainable Artificial Intelligence. This paper reviews the enabling technologies for Industry 5.0 and suggests some pertinent research areas requiring more focus. The transition of manufacturing processes from mass production to mass personalization, the anticipated reliance on Cyber-Physical Systems (CPS) and digital twins is visualized, to identify the gaps in fully realizing the revolution. The operations of smart factories to enhance the overall productivity, modern workforce comprising of human-machine collaboration, means of heterogeneous data transmission & data interoperability, and security & privacy issues are reviewed to identify hot research spots, that will eventually fill in the gaps within societal domains to realize Industry 5.0. The potential of the new domain of Explainable Artificial intelligence to understand the application of right tools in a data connected Industry 5.0 compliant smart society is explored. Altogether, this research explores several research challenges and opportunities linked with IR 5.0.

Keywords: Smart Society, Explainable AI, Big data analysis, Cyber Physical System, Digital Twins, Cloud Storage

1. Introduction

The term industrial revolution (IR) refers to the technological advancements introducing novel ways of living that drastically transform the society. This revolution process began by first industrial revolution (Industry 1.0) and was characterized by steam engines. This was the base of the technological revolution (Industry 2.0) that allowed more outstanding production with the help of mechanical machines. The application of IT processes in production led to the third industrial revolution (Industry 3.0), enabling the automation of entire production process. The concept of mass production was introduced during Industry 3.0. The production systems already benefiting from computer technology fueled the digital evolution (Industry 4.0) of the past decade by incorporating new technologies: robotics, artificial intelligence, deep learning, augmented reality, cloud technologies, 3D printing, for mass production. A major milestone was the improvement in network connectivity of manufacturing and production systems, taking the production automation to another level. This digital evolution of the past decade has laid the foundation for the human-machine coworking era (Industry 5.0), pertaining to increased collaboration between humans and smart systems to address mass personalization while improving the work efficiency. The European Economic and Social Committee (EESC) describes Industry 5.0 as a combination of human beings' creativity with robots' speed, productivity, and consistency. The vision is to strive for a *human-centred* society by an enhanced partnership between humans and smart systems. With this partnership, machines take over the monotonous, tedious, and repetitive tasks, while machines' increased supervision and creative jobs rests with humans. This will raise the production quality across the board. In that regard, the menial administrative work

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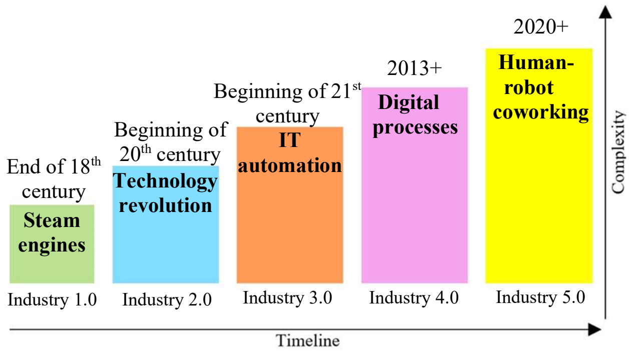

Figure 1. Industrial revolutions

is already being performed by robotic process automation (RPA) tools, 3D printing is already prevalent, and chatbots are increasingly being deployed to serve the customers. In IR 5.0, there will be increased collaboration between humans and smart systems like robots. The authors in [1] interviewed eight different industries to conclude that IR 5.0 will impact the businesses in terms of collaboration between humans and smart technologies. The amenities will be transformed into the Internet of things (IoT)-enabled smart facilities utilizing cognitive computing. e.g., sensors collecting the data autonomously to track when and how an individual cooks his meals or how often they use other home gadgets. To that effect, digitization (characterized by Industry 4.0) is already being evolved into personalization in various industries, where multi-level cooperation between people and machines is increasing to enhance the overall throughput. To achieve such a technology-based, human-centered society, it will be necessary to overcome digitalization challenges by bringing together a diverse group of stakeholders that share a single future vision for personalization, workforce, efficiency, and interoperability. This vision can be realized by the quality and meaningful information generated in cyberspace by employing efficient deep learning techniques to the data collected by sensors and then using that information in the physical world. This fusion of physical and virtual worlds is called digital twins and is predicted to develop in a trillion-dollar market in the next five years [2]. Digital Twins extends on the concept of employing simulation modelling at all stages of a project's development. Bringing real-world data together with design simulation models will enable precise and economical production and prediction based on real-world data. Smart infrastructure, an essential component of Industry 5.0 smart living, is equipped with wireless sensor networks for smart monitoring. The devices of the smart infrastructure are connected to a cloud-based system that processes the data monitored by sensors. The notion of transferring the sensor data to the digital twins at the cloud platform to receive the processed useful information has the potential to improve people's lives while maintaining sustainable economic growth. However, the bandwidth required for the hyper-seamless connectivity that enables small devices to communicate in such a context-aware smart society is a challenge. The Internet2 [3] consortium has the promise to address this high-performance requiring bandwidth challenge. To future proof the success, innovation is the key. The Artificial Intelligence (AI) and RPA tools assist in decision-making processes across numerous industries. The black-box nature of these systems allows accurate prediction mechanisms [4]. However, in life-threatening scenarios (health care, national defence, autonomous vehicles), an insight of the internal mechanism is required. This insight is achieved via Explainable Artificial Intelligence, which aims to create more explainable AI algorithms while maintaining high-performance levels [5]. There has been some effort to employ explainable AI techniques in context-aware computing paradigms to construct smart society comprising of smart homes and cities [6]. However, it is a challenging task to keep a balance between accuracy and explanation of an AI model [4]. We discuss more about explainable AI approaches, applicable to IR 5.0 in Section 4. The rest of the paper is organized as follows: The focus of the next section is to review the ongoing efforts towards resolving various societal challenges for the organizations, people and society, by incorporating technology tools. This review of societal domains helped in identifying the technology gaps towards Industry 5.0 transition. Section 3 cites the opportunities and the associated challenges to address the identified gaps. We discuss the relatively new concept of explainable AI in Section 4 and provide some insights into the means of incorporating explainability into AI algorithms for Industry 5.0 applications. We summarize our ensemble effort meant to ensure that no one is left behind in the new high-tech world of Industry 5.0 and conclude in Section 5.

2. Literature Review

The IR 5.0 holds the promise to solve societal problems, such as natural resource exhaustion and economic disparity across the world. We can achieve this target by acquiring new knowledge and generating new values that could connect people and things. This will create a resource efficient smart society with better lifestyle for its residents. The optimized resource planning for smart societies is discussed in [7], where a planned energy efficient smart city uses a hybrid smart grid that achieves energy efficiency by optimizing connected devices. As IR 4.0 was primarily focused on mass production using robots, machines and other digitized systems, IR 5.0 brings back the humans at the core of the production processes. The issues when humans work with robots and factory systems [8] would lead to a new IR 5.0 employment market, which is visualized in [9]. There is significant progress at collaborative engineering robots [10] that would enhance human craftsmanship. Xu presents an industrial information integration that is transdisciplinary between cyber-physical systems, IoT, and cloud computing and then explores each of these disciplines with technologies employed [11]. In human-machine collaboration, information security and confidentiality at work will become a multifaceted concern. It will be an essential research area in information security. IR 5.0 will blend the human intelligence and creativity with smart, digitized, and advanced industrial processes, which will result in personalized products. The market feedback indicates that the human craftsmanship in Industry 5.0 would be inevitable, as there is no alternative to human intelligence for minimizing the mistakes and errors, thereby preventing losses. The fifth industrial revolution is characterized by combining human intellect with the highest standard of digitization, to optimize the human efficiency. Industry 5.0 will take personalization of the end products to a new level. This will ensure the customer satisfaction and will lead to sustainability by ensuring new product and job opportunities, for all the residents of the planet. In that framework, this section reviews the above discussed notions in various societal domains. We focus on the human centered technology applications that connect people with things that would eventually lead to IR 5.0.

A. *Smart Societies*

Human centered smart societies will be an inevitable component of Industry 5.0, aiming to improve the quality of life for all individuals. The aim is to build a society in which all citizens, including people with disabilities & intractable diseases, are dynamically engaged and demonstrate their full potential. The ambitious policy program of Japan Society 5.0 [12] plans to use technology tools that create the infrastructure and connections between systems and technologies to transform society. In Society 5.0, a massive information is collected from sensors in real world. This big data is sent to cyberspace, which is analyzed by sophisticated machine learning techniques. The results are sent back to humans in real world in various formats. There has been some groundwork to envision the Society 5.0. The Lumada platform [13] uses large volume of data to extract new insight to create customer innovative solutions. The smart cities can be considered a subset of smart society. In a smart city, the application domains are categorized in six groups: natural resources & energy, transportation & mobility, infrastructure, living, governance, and industry & human resources [14]. The emergence of fifth generation IoT makes it possible to process big data at increased rates for cloud computing platforms [15]. This together with explainable AI has paved the path to smart society applications such as smart logistics, smart vehicles, smart agriculture, smart energy infrastructure, smart transportation, smart health care, and smart online

TABLE I: RECENT PROJECTS ABOUT SMART SOCIETY

Project	Objective
Smart car parking [16]	An IoT middleware that finds the best free parking lot
City4Age [17]	An IoT based storage solution to promote healthy ageing
RADICAL [18]	Analyze big data for carbon footprint monitoring, urban noise measurement & other applications for urban services
Urban surveillance video streaming [19]	Real time information processing & decision making
IBM Smart City Project [20]	Adopt Open Innovation approach to create a clear vision of smart city across the globe
WHO Healthy City Project [21]	An IoT based project focusing on well-being of the residents of smart society
Smart Logistics [22]	RFID, WSN and ZigBee based logistics (freight transportation, warehousing and delivery) operations
Smart surveillance [23]	Genetic Algorithm based high detection ZigBee surveillance sensor system
Smart energy infrastructure as a service (SEIaaS) [24]	An AI based framework for Renewable Energy focused on economic efficiency and sustainability

systems. Table 1 [16-24] captures some of the projects focused on elevating the living standards in a smart society. The focus is to improve either one or more of the above-mentioned application domains of the smart society. There has been a considerate amount of investment during the last decade to transform numerous cities to a smart society. Smart City 2.0 is Ottawa's Smart City Strategy [25]. It is centered on three goals: achieving a connected city, a smart economy, and an innovative government. The City of Toronto has several smart initiatives to ensure that its residents are digitally connected to the local government's services. These initiatives include: COVID-19 chatbot, automated water meters and an open data portal with 30 datasets in varying formats [26]. The 2017-18 Seattle IT Strategic Agenda [27] aims to transform Seattle into a data-driven city. Some of the objectives are implementing the digital equity action plan, creating user-centric solutions that connect the Seattle residents with their government, developing the city's workforce to evolve with technology, engaging the partners and the community to develop new technology solutions to promote the strategic uses of new technologies. Smart society, however, has a broader scope than a smart city. The scope of a smart society aims to solve the 17 United Nations' Sustainable Development Goals by 2030 [28]. The researchers are working to create an environment where these 17 goals are met by incorporating technology into mobility and infrastructure. This will result in an empowered society, where community functions at an elevated level and the social challenges are resolved by incorporating technology innovations into society. The academia and industry are working to address certain challenges to achieve the goal of a smart society. In a data-driven smart society all the infrastructure is interconnected to a single network. A resilience mechanism to eliminate the possibility of a single point of failure in the network is needed. Ahmed in [29] identifies the research challenges of IoT based smart interconnected cities. Anand [30] analyses the civil infrastructure obstacles for developing nations to achieve the goal of smart society. These efforts demonstrate the advanced technology solutions to create new values, targeted towards building diverse industries to foster innovation, enabling society members to enjoy higher quality of life.

B. Drones

Originally, drones were employed in military applications, but today drones are already used for real state & aerial photography, industrial inspection, agriculture, insurance and state & local government applications, as depicted in Figure 2. More recently, drones can connect to highspeed internet networks like 5G, allowing drones to communicate effectively with their user anywhere if there is signal coverage. These capabilities have expanded the drone applications areas. Soon, drones will be widely employed in public advertising, deliveries, sports entertainment, emergency response, and to supplement human capabilities. Commercial airlines have also started partnering with drone delivery companies to develop innovative logistic solutions [31]. According to The United States Federal Aviation Administration (FAA) [32], by the end of 2020, there were more than 488,000 commercial drones registered in the FAA database. This was an 8.5 % increase from 2019, which can be attributed to decreasing equipment prices, improved technology such as built-in

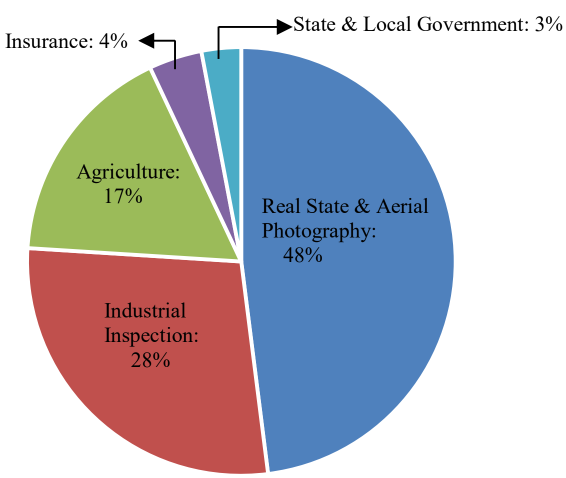

Figure 2. Commercial drones' usage, per FAA

cameras and higher capability sensors. However, numerous challenges still need to be addressed. The integration of civil and public drone operations into the

Figure 3. DJI drone for aerial photography

National Airspace System (NAS) is a real challenge. It will continue to grow with drones being employed in previously envisioned applications. This challenge is evaluated in Integration Pilot Project [33]. The authors in [34] compare contemporary commercial off-the-shelf drones with current drone models' maximum specifications. Most of the available studies on drones employ Parrot ARDrone, as their API, that is simple to use, facilitated quick prototyping [35]. This model, however, is already discontinued by the manufacturer. Therefore, the future progress in the domain of an open-source drone dedicated to investigating control modes would be a significant contribution. The DJI drone shown in Figure 3 dominates the market for aerial photography. It can reach the maximum flight time for a commercial drone. Commercial drones that are currently available have flying times of up to 31 minutes and speeds of up to 93 kilometres per hour [36]. The time and speed of current drones are also expected to improve with the hardware and software advancements. Human Drone Interface (HDI) is a research domain still in its infancy and holds the promise for significant contribution in the IR 5.0 paradigm. Conventionally, drones were operated by a joystick or a ground control station; however, research in HDI has led to novel natural user interfaces such as gesture-based control [37], brain-computer interfaces [38, 39], speech

TABLE II: CHALLENGES WITH DRONE CONTROL INTERFACES

User Interface	Challenges
Joystick	• Less intuitive
Gesture	• Collocated interaction only • High latency and lower control precision
Speech	• Collocated interaction only • Propelller sound can impact speech recognition • Not all drones are equipped with microphones
Brain-Computer Interface (BCI)	• Longer training periods • Lower control accuracy • Slower input and output response
Touch	• Collocated interaction only • Requires safety measures
Multi-modal	• High cost • High complexity

recognition [40], touch [41], and a combination of multiple modes [42, 43]. Each control interface has its own challenges, which are summarized in Table 2. Further research is needed to address these user-interface challenges and find new ones. An experimental study [44,45] concludes that cultural differences impact the drone interface choices, e.g. Multi-modal contact with drones is preferred by 45 percent of Chinese users against 26 percent of American users. Future research could focus on extracting design criteria to ensure that future drone technologies are well-received by the general public.

C. Healthcare

Smart healthcare refers to wearable smart gadgets and networks to improve healthcare services. The gadgets constitute the Wireless Body Area Network [46] meant to collect the real-time medical data that is then transferred seamlessly to the IoT cloud computing health platform. The transferred data has cognitive features incorporated using Simulated Annealing [47] and Artificial Neural Networks [48]. The cognition features help in responding intelligently to medical ecosystems [49]. In that regard, machine learning-based diagnosis systems are proven to be more accurate than human doctors [50]. Kumar in [51] proposes integrating Blockchain 3.0 and Healthcare 4.0 processes to simulate a smart healthcare system. A diverse range of smart healthcare applications have been reported in the literature. The authors in [52] focus on different IoT based healthcare systems for WBAN. A ubiquitous healthcare framework is proposed to address the challenges of delivering anytime anywhere healthcare services. The realization of next-generation healthcare is investigated by developing a proof-of-concept system, UbeHealth, which leverages deep learning, big data and high-performance computing and addresses the challenges of latency, bandwidth, and energy consumption [53]. Smart wearable healthcare devices have led to a Personalized HealthCare System (PHS). Examples of such PHS are systems that deliver medication on the fly; systems that enable remote monitoring of patients, and systems that support the movement of individuals with disabilities [54, 55]. The 7P features [56] (personalized, persuasive, predictive, participatory, preventative, perpetual, programmable) have transformed healthcare towards a data-based patient-centric approach by incorporating RFID, biometrics and metering devices. In [57], IoT based wearable devices are used for remote patient monitoring and medical assistance. In [58], wearable devices communicate with cloud servers that can be accessed remotely via the internet. The information communicated by the wearable device includes heart rate, amount of sleep and physical activities. In [59], a voice pathology detector is proposed to distinguish between voice and electroglottographic (EGG) signals and then transfers to the doctors using a cloud computing platform. There have been some efforts in developing health monitoring environments. A smart city infrastructure that supports strategic healthcare using machine learning techniques is proposed in [60]. Such ambient sensor-based systems are already functional to capture and monitor health-based information [61]. The adaptation of IoT based smart homes for elderly healthcare monitoring is discussed in [62]. The short-range and long-range communication technologies will be used to transport data between devices and servers in Industry 5.0 healthcare systems. With the advancement in these communication technologies, more modern healthcare solutions are anticipated, e.g., surgeons can perform virtual operations with robots from anywhere in the world [63]. The authors in [64] identify the research challenges for such telesurgical systems. The enabling technologies of Industry 5.0 that exploit 5G smart healthcare taxonomy is reviewed in [65]. Those technologies include software-defined network (SDN) and network function virtualization (NFV) for 5G smart healthcare.

D. Autonomous vehicles (Internet of Vehicles)

As vehicles evolve from simple transportation means to smart entities, they will be an integral part of Industry 5.0. The US Department of Transportation's National Highway Traffic Safety Administration (NHTSA) predicts that by 2030 level-5 fully autonomous vehicles [66] will account for 15% of the global automobile market. The research progress on self-driving cars, e.g., AI-based algorithms for path optimization, [67] and identification for obstacles on the road [68] indicate the shift towards that direction. Industry 5.0 smart vehicles are expected to safely self-drive, employing sensor platform that have the following modes of communication: Vehicle to Roads (V2R), Vehicle to Person (V2P), Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I). They can be considered a superset of Vehicular Ad-hoc Network (VANET) [69]. Guan in [66] focuses on IEEE 802.11p standard to study the path loss, shadow fading and delay spread of the channel for small scale and large scale road structures. Campbell in [70] proposes sensor fusion techniques to increase the vehicle's perception and autonomy. A scheme for Vehicle to Anything (V2X) short-range communication has been evaluated in [71]. Currently, almost all major automobile manufacturers worldwide are engaged in autonomous vehicle commercial solutions. Level 3 autonomous features [66] such as on the fly communication and adaptability are already available. BMW via a series of sensors monitor vehicle information such as battery voltage and driving trajectory. Tesla cars employ the cellular connectivity to upgrade the automotive software through cellular and WiFi connections. The future automatic vehicles would consume and generate big data. The Google Driverless car is already known to produce 1G of data per

Figure 4. V2V using sensor platforms

second. The huge amount of data generated for a future automatic vehicle calls for the need of advanced data processing tools such as Hadoop distributed file system and apache Hadoop MapReduce. The authors in [72] discuss the network characterization and protocol design of IoV and explore the big data acquisition, transmission, storage, and computing for future IoV. The basic three-layer architecture of IoV is described in [73], which is then enhanced into a seven-layer architecture in [74]. The five-layer architecture of the Cognitive Internet of vehicles is presented in [75] that realizes control and decision making for future autonomous vehicles by incorporating intelligent cognition. A case study based on cognition of fatigue driving shows promising results. In [76], the data-driven algorithms are exploited for decision-making in autonomous vehicles. The complex perceptual models where decisions are made in scenarios that are not included in the training examples are considered to account for unpredictable situations on the road. Deep learning algorithms have shown encouraging results in applying the previously learnt rules to new scenarios, making them viable for autonomous vehicles. An autonomous driving system is proposed in [77]. The system uses a combination of deep Q-learning [78] and previous driving experience. Another effort to develop an autonomous braking system employs Deep Q-Network (DQN) to optimize the conflicting objectives of avoiding collision and getting out of high-risk situations [79]. The work was extended in [80] by using a deep reinforcement learning algorithm to control velocity and steering. Despite being efficient for quick decision-making in autonomous driving scenarios, deep learning algorithms have their own set of challenges. The black box problem [81] makes it impossible to test all the unpredictable road scenarios that an autonomous vehicle might encounter in real world. Explainable Artificial Intelligence algorithms are a potential solution for this block box problem. Other challenges associated with deep learning algorithms include training time, computation requirements and optimization of conflicting objectives. Once these challenges are addressed, the autonomous vehicles will have major impacts in terms of urban sprawl, road infrastructure, parking spots and even the appearance of the vehicle. [82]. Industry 5.0 compatible IoV will likely be driving on public roads in the near future.

E. Financial Technology

Financial Technology (FinTech) refers to personalized financial services innovation by deploying AI, big data analytics, quantum computing and smart contracts. The advanced FinTech payment solutions by technology companies like Apple Pay and Google Wallet are already improving the quality of financial services. Data-driven insurance [83] and automatic trading [84] are examples of niche-personalization of financial services by employing AI and big financial data processing. Lee in [85] discusses the six fintech business models and explores the challenges associated with each model. The emerging FinTech solutions like cryptocurrencies are challenging the role of intermediaries, such as governments or brokers of traditional currency. In this context, the overlapping of cryptocurrencies with crowdfunding – financial systems without intermediaries – decouples economic activities from physical facilities. The zero trust networks and humanoid robots further add to the location independent secure access. Financial institutions such as banks, crowd funding wealth management companies and insurance enterprises are adapting their customer services to FinTech offerings. The development of the financial sector in smart cities will ease access to other facilities such as health, education, business and strengthen human capital [86]. The rules of customer interaction in Industry 5.0 digital finance cyber-physical systems are likely to be managed and controlled by machines. Predicting financial risks using intelligent agents is an example of applying FinTech to take informed financial decisions [87]. Yan in [88] uses convolution neural networks to model time series that forecasts stock index. The excitation function used was Sigmoid, and the training process used was forward propagation and backward propagation. The simulation results showed accurate prediction results. Chen in [89] proposes a Robotic Process Automation (RPA) based enterprise financial reimbursement method that is helpful in audits. However, the algorithmic failure in deploying RPA based robo-advisors for the wealth and stock management may expose customers to security and privacy threats. Moreover, the FinTech industry has widely accepted cloud computing as it decouples financial activities from physical infrastructure to offer location-independent safe access through the use of technologies like zero-trust networks. The web-based service model of cloud computing has its own challenges such as physical location of cloud servers, lack of data control and financial frauds in web-based service model. There is a serious need for new technology and cryptographic methods to make the FinTech systems more secure. Yu [90] develops a three-tier enterprise financial management system that collects and organizes the data in reports detailing financial statement statistics. The web-based system makes it convenient to query the relevant financial data for audit purposes, thus eliminating the financial fraud. The regulatory requirements governing the FinTech business models and their operations will significantly impact the growth of Industry 5.0 FinTech systems. The regulatory requirements vary from country to country. The cryptocurrency-related transactions are illegal in China while encouraged in Venezuela. The quest for man and machine working together to make the best financial choices, discovers the maximum level of the overall financial well-being in Industry 5.0.

F. Farming (agriculture, forestry and fisheries)

The farming sector includes the food-producing domains of agriculture, forestry, and fisheries. These sectors are already incorporating smartness to head towards the Industry 5.0 revolution. The robots are already being used for crop harvesting. e.g., FFRobot [91] can pick upto 10,000 fruits per hour. The fish catch production is increased by smart fishing tools such as Vessel Multi Aid [92]. John Deere manufactures the automatic driven IoT based tractors with cloud computing capabilities. Vertical farming [93] and hydroponic [94] techniques address the shrinking of agricultural land and water shortage, by increasing farm production multiple times and consuming upto 95% of less water. These techniques are further enhanced by using sensors that analyze the crop related parameters. Acoustic sensors are used for pest detection [95]. Ultrasound ranging sensors are used for monitoring crop canopy [96], Airflow sensors measure soil air permeability by using moisture levels and other unique measures [97]. Electrochemical sensors analyze the pH, salinity and other soil nutrient levels [98]. Soft water level-based sensors characterize water level and flow by measuring rainfalls and stream flows [99], thereby addressing the drought related concerns. Optical sensors detect the fruit maturation [100]. The sensors can also be used for forestry and fishery applications such as forest disaster monitoring and fisheries farm water analysis. The satellite remote sensing can be combined with ground-based sensor data for fire prediction and monitoring [101]. The water quality parameters for smart fisheries farming can be detected using available sensors. Akhter [102] proposes a cost-efficient Agriculture 4.0 compliant system that monitors water quality factors for smart fisheries. The water parameters measured by the system were pH, nitrate, phosphate, calcium, magnesium and dissolved oxygen in water. The nitrate concentrations were measured in an Australian lake that showed promising results. Each of the mentioned sensor has its own data format, temporal characteristics, and size. The storage of remote sensing data in clouds is another challenge. Industry 5.0 smart farming system must be capable of processing and learning from increasing data volumes in multiple formats, to take informed decisions. The big data obtained for forestry monitoring relies on UAV and wireless sensor networks [103]. This big data, when processed using computing frameworks like Spatial Hadoop, can improve informed decision making in landscape mapping, timber yield forecast, plant diseases detection, weed control and irrigation assessment. In order to process big data, there have been applications of deep learning in agriculture and forestry. E.g., the plant disease detection gave an accuracy of 95.8% after 100 training iterations using Convolutional Neural Networks [104]. CNN was also employed to predict agricultural yield [105]. Namin in [106] performs plant phenotyping by extracting the plant features using CNN and then feeding the extracted plat features into Long Short-Term Memory (LSTM) network. The sequence model improved accuracy to 93%. Das [107] targets smart image interpretation by proposing a spatiotemporal prediction method for data obtained by satellite remote sensing. The use of sustainable IoT based sensors, cloud computing-based decision systems and deep learning applications to process the big data collected by the sensors is not an optional – it is necessary in the farming domain as it drives the nations' livelihood.

G. Sports and Physical Education

The Industry 5.0 revolution aims to create an innovative sports society by integrating virtual augmented reality and machine learning with sports activities, thereby improving people's health and fitness. The wearable smart sports products, such as Fitbit's fitness monitors and Nike's adapt smart basketball shoes, are already available in the market. The emergence of intelligent wearable sports products that capture the players' movements using sensors and the associated challenges: short life cycle, high energy consumption, absence of standards and nomenclature as to what classifies as smart, and data privacy issues are discussed in [108]. The basketball player health monitoring and performance enhancement is discussed in [109] by presenting a ZigBee based on-body nodes wireless body area network with limited sensors (temperature, humidity and accelerometers). The proposed system is scalable to incorporate other sensors and has been tested under real conditions during a match. MySwing Professional [110] is a golfer training system equipped with 17 wireless full body sensor nodes with cloud storage capabilities. Besides wearable devices, another way to obtain the sensory athlete data is by developing smart sports equipment with embedded sensors. A smart soccer ball prototype is tested on mannequin to flag potential head injuries during headers in soccer [111]. The smart ball is yet to be tested on real players. The applications of AI in sports training are discussed in [112] implying that sports training no longer just happens on the playground. The IoT smart sports classroom diversifies the learning experience while meeting the individual fitness needs of all the trainee athletes. In that regard, Lei [113] investigates the promotion of Chinese martial arts-based fitness guidance. The fitness digital classrooms employ augmented virtual reality and intelligent fitness equipment. Xie [114] designed an intelligent badminton training robot that recognizes the athlete's movements to prevent the injuries. The hidden Markov model-based robot achieves a recognition rate of 94.5%. However, the data mining and analysis on the athlete training data in a cloud platform is not addressed. In another research, Lee [115] investigates physical self-efficacy by employing virtual reality tools to conduct T-ball lessons and infers a positive impact on physical education diversification on students. A commercially available virtual reality-based training platform called QB SIM [116] mimics real rugby stadium for the trainee athletes. Whether it is smart devices, intelligent equipment or virtual training platforms, the smart sports industry is inseparable from data analysis and mining. After analyzing health-related data, the prediction algorithms can effectively improve the individual's fitness. In that regard, Zhang [117] employed a combination of fusion decision tree, K-means spatial clustering and naïve Bayesian data mining methods to investigate big data consumption in the sports industry. Wang [118] analyzes the consumer demand in China for physical fitness under the big data paradigm and concludes that physical demand is constantly expanding despite the information security concerns. Chu [119] proposes an Artificial Intelligence of Things sports system that contains multimodal sensors mounted on sports equipment and the athlete. The sports IoT system transmits the collected data to sport informatics and analysis system (SIAS) residing in cloud and employing deep learning algorithms. The advice for the athlete is retrieved from SIAS. By incorporating intelligence in sports and physical education, the fitness and well-being for all members of the smart society can be improved. This in turn will ensure an active and healthy life for all at all ages, thereby realizing one of the most important goals of the UN's Sustainable Development programme [28].

Figure 5. Wearable smart device with heart health (ECG), stress management and skin temperature trends measurement tool

H. Transportation systems

Industry 5.0 intelligent transport system (ITS) would be built on smart sensor, big data, and deep learning technologies to increase environment sustainability and improve community health. Canada is aiming for a zero-emission transport system by 2035. A variety of data collected from smart sensors in an ITS is already approaching to Petabytes. Automatic Fare Collection (AFC) systems deployed in citywide rail systems captures data about individual travelling patterns. GPS data is used for dynamic route guidance by monitoring traffic. Ultrasonic and acoustic sensor systems, light detection and ranging (LIDAR) and video image detection systems collect data from roadsides [120]. Infrastructure related data such as smart grid can facilitate the daily electricity usage data for trains and buses in urban rail transportation. The collected data can address many traffic issues, such as travel delay measurement [121], predicting congestion probability, or estimating the occurrence of traffic accidents. For example, in [122] recurrent neural network and restricted Boltzman Machine is used to predict the traffic congestion based on the data collected from taxi. Lin [123] forecasts the spatiotemporal traffic congestion data to determine a congestion-aware path in the software-defined smart city paradigm. Zheng [124] used social media data to develop a traffic sensing and analyzing system but reliability of data collected using these social sensors [125] remains a concern. In [126] Support Vector Machine is used to predict traffic accidents. However, the prediction accuracy depended on kernel function parameters and trial and error method was employed to choose the appropriate kernel function, which is not viable is real-time applications such as accident prediction. A German Startup 4pilots [127] addresses real-time concerns and reports data regarding bad driving behavior (intoxication, rage driving or drowsiness). The collected data is stored in a cloud server from the edge and retrieved using Message Queuing Telemetry Transport (MQTT) to ensure network reliability and security. Several neural network techniques are used to classify and predict the data in real-time. However, in fully autonomous vehicles, the need of human drivers will not exist anymore, rendering the driver emotions capture technology obsolete. An example of such robocab service is 5G Remote Driving Service recently rolled out by Baidu [128] in China. Although it is an autonomous driverless taxi service, operators can remotely access the taxi in case of an emergency. With the IoT, new sensor techniques are emerging, and those new developed sensor techniques can be used to collect new variety of data. This data can be processed to obtain helpful information leading to Smart Society 5.0 initiatives. The railroads and airlines manage passengers and routes through cloud platforms. These cloud platforms store and process the big data to predict the ITS scenarios accurately. A big data simulation platform is proposed in [129] for Toronto region that runs the big data transportation applications in real time. Hadoop is a promising platform for data collection - AFC smart cards, sensors, social media, and GPS - processing. The speed and quality of the diverse collected data and its efficient processing would help to accurately predict the traffic flow, accidents, bus schedules and efficient travel routes. The prediction methods for ITS are summarized in [130]. The deep learning models [131] have shown good performance in predicting ITS related big data, such as traffic flow density [132]. Yin [133] proposes a smart train operation method which combines data mining algorithms and manual driving expert knowledge. The big data already approaching Petabyte and continuously increasing volume and variety pose another challenge for cloud storage providers. Multi-cloud storage solutions that incorporate intelligence are emerging as key solutions for ITS. The speed, quality, and learning mechanism applied for big data processing techniques for cloud platforms are playing a key role in the realisation of an industry 5.0 intelligence transportation system. The robocab and software defined train prototypes are all made possible because of the progress in sensor, big data and deep learning technologies discussed above.

I. Art, culture and tourism

The usage of AI for art design incorporates aesthetics and diversifies art and culture. Industry 5.0 art design will be more convenient to create and integrate machine learning and augmented reality technologies. Artists are already incorporating innovative designs using AI in their artefacts - painting, poetry, music, movies, and fashion design. For example, a machine learning algorithm that had been trained on 15,000 pre-20th century portraits was used to create the painting: *The Portrait of Edmond de Belamy*. [134]. Other examples of generating Industry 5.0 compliant art designs include: AI generated trailer for the film *Morgan* [135], Deep learning-based commercial advertisement banners launched by Alibaba [136], Neural Networks algorithm of Amazon that automatically generates modern clothing designs [137]. Museums, cinemas, and entertainment industry are increasingly turning to augmented reality technology to present their exhibits. The ability of big data and cloud computing to collect, analyze and train the systems is the basis of emotional computing framework application in the broadcasting and media industry. Such computing frameworks are already successfully deployed in broadcasting industry. Xiaoice [138] a virtual TV anchor was the pioneer in synthesising real-time AI audio and video processing in the electronic media industry. EduRobot [139] is an entertainment chatbot with singing and storytelling capabilities. However, both Xiaoice and EduRobot lack empathetic capabilities, excluding them for senior citizens. The social inclusion of elderly people is an essential component of Society 5.0. To reduce the digital gap for the elderly, Garcia-Mendez [140] designs an interactive news services chatbot. The design comprises of natural language generation and sentiment analysis using advanced deep learning algorithms: gradient descendent, decision tree, and random forest. The chatbot prototype was tested on 31 users in the age range of 68 and 82 years and the chatbot prototype received a satisfaction score of 4 out of 5. Intelligent chatbots are empowering travel agents to promote smart tourism. These chatbots are deployed in social media applications to offer travellers a more personalized experience. Various other research efforts propose machine learning for touristic purposes. The K-Nearest Neighbor is used to develop a smart travel map based on tourist preferences such as culinary, accommodation, budget, facilitates and destination distance [141], and to produce three recommendations with an accuracy of 73%. The logistics costs of touristic destinations in Peru are accurately forecasted using artificial neural networks [142]. The intelligent health tourism modelling is done using Markov Chain Model [143]. AI and augmented reality have also set foot in performance arts such as theatre and dance. The ballet dace movement for humanoid robots is modelled as an optimization problem using a state transition model for each ballet pose [144]. Ozcimder [145] studies a humanoid robot representation of dancers by developing an AI prototype system to assess the artistic merit in human dance performers. The AI judge assigns a score based on the metrics for the salsa dance detected sequences, represented by a finite state machine. The AI judge uses the score function to evaluate the performance based on energy consumed by the dancers and the diversity of the moves in the performance. The creative thinking of artists, when combined with deep learning and big data, can generate

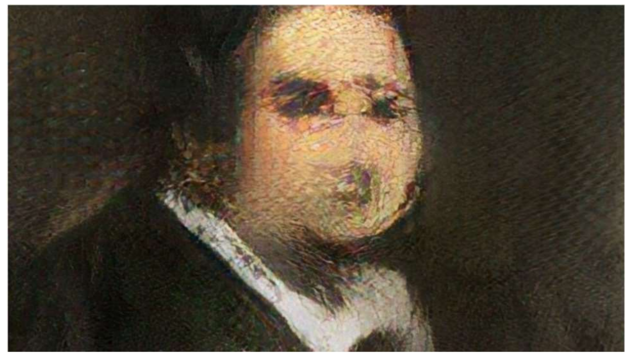

Figure 6. The portrait of Edmond de Belamy drawn by AI

very sophisticated artwork that enriches the culture and provides quality entertainment.

J. Construction,

The smart infrastructure compliant with Industry 5.0 comprises of new technologies in construction industry, such as modular construction, 3D printing and augmented reality. Building information modeling (BIM) is a prominent digital planning method in construction. The managerial construction tools and activities [146] can be integrated with BIM environment by using BIM360 API, to achieve better material handling. Wang [147] analyses the BIM integration with other technologies such as laser scanning, photogrammetry, virtual reality, and RFID to observe improved construction data analyzing efficiency. This integration can be used to create a digital twin of the construction structure. The digital twin data is saved and processed in cloud platforms and collected using various sensors: strain sensors [148] characterize the structural health of components, barometric sensors [149] monitor the construction elevators state and other machinery operation, acceleration sensor [150] measure the carbon emission of the construction material, fibre optic sensors [151] automate the supply chain management process by activating the RFID reader on the construction material. The sensors are also used to evaluate factors that make construction work challenging, such as weather conditions. Wind and rain sensors [152] are used for wind speed and rain load monitoring. The captured data is then visualized in a cloud processing platform [153]. Virtual reality techniques have been used in construction risk analysis. E.g., crane lifting more safely and efficiently to enhance the site safety [154]. The manufacturing method for irregular surfaces is employed using computerized numerical control (CNC) T-BAR system [155]. The CNC T-BAR system uses computer-calculated planer figures and other drawings read by robots and then cut iron bars (T-BARs). The research concluded that higher-level construction skills will be more in demand with a high-end technique aligned with Society 5.0 goals. 3D Printing is used for sustainable construction by improving accuracy and saving time and costs, compared to the traditional method [156]. The MX3D has built an intelligent bridge using 3D-printer [157]. The steel bridge is equipped with numerous sensors that collect data about strain, displacement, vibration, air quality and temperature to monitor the structural measurements in real time. The cloud computing and machine learning algorithms are employed to incorporate intelligence in the bridge that reacts to a change in its environment. Carra [158] presents a survey of robotics in construction sites in numerous domains such as building cladding and structuring, together with technology trends: 3D printing, BIM, circular construction model and remote machine operations. Wearable devices aimed at construction workers' safety in heavily unstructured construction sites are also important. Kanan [159] designs a wearable device weighing 55 g that prevents fatalities within a radius of 4 m by warning the worker about the nearby hazard, such as a vehicle detected by radiofrequency (RF) field. The wearable device contains radio transceiver, a wakeup sensor and a GPRS module. However, in a Society 5.0 safe environment, machines will be employed to do the risky and repetitive construction tasks, eliminating the need of wearable devices for construction workers. There is a huge potential for the construction industry to improve productivity by applying emerging technologies in the Industry 5.0 revolution, thereby improving safety, reducing cost and supporting affording housing for all Society 5.0 residents.

Figure 7. The world's first intelligent bridge by 3D printer

TABLE III: IDENTIFIED GAPS IN MULTIPLE SOCIETY DOMAINS TO REALIZE INDUSTRY 5.0

S.No.	Domain	Type of Research Contribution	Research Year	Research Limitations	Research Gaps to realize Industry 5.0
1	Smart society	Human-robot coworking to create personalized products [9]	2020	The future vision for legal, social, regulatory and ethical concerns is not backed by any data due to the dearth of real time human-robot coworking use cases	• Development of high end skills aligned with smart society goals, such as qualified workers to employ in 3D printing construction environments • Flexible production planning and inventory management by establishing links with other fields and industry

					suppliers outside of one's usual business dealings
		Big data transfer to cyberspace, which is then analyzed by cloud computing platforms [15]	2020	Data heterogeneity: Data collected from multiple domains, applications and environment parameters has no uniform standard to follow	• High bandwidth requirment to address the high performnce needs of big data transfer • Black box deep learning mechanisms with no transparency
		A hybrid smart grid simulation that achieves energy efficiency by optimizing connected devices. [7]	2021	The real hybrid smart grid might need additional parameters consideration for calculating latency factors while generating reading from different sources (photovoltaic, hydro, and thermal power)	• Energy savings by optimizing energy use based on supply predictions
2	Drones	Drone contol modes design [37-43]	2010 - 2019	Each mode has its own set of challenges and requires a compromise based on user choices [23]	• Different sensory modalities (visual, auditory, haptic) have different requirements for sampling, transmission rate, latency, reliability.
		Drone delivery companies partnership with commercial airlines [31]	2021	The drone logistic standards are vague or non-existenet. The regulatory authorities (e.g. Transport Canada) are in the process of regulating drone logistic standards such as limits on package size, delivery distance and liability in case of material stealing or destruction	• Expansion of drone application areas e.g. perform optimal delivery of relief materials in natural disasters, deliver farm produce to consumers when needed and automate collection of crop data through drones • Increase the commercial drone capabilities to meet the smart society objectives
3	Healthcare	Feasibility of IoT based smart homes for elderly healthcare monitoring [62] Ubiquitous healthcare by delivering anytime anywhere healthcare service [52]	2018 & 2019	Architecture limitataions leading to concerns, such as: data integrity preservation, and remote adverse effects on data sharing if patient's devices start malfunctioning or its battery discharges. The subjects (elderly people) should represent more diverse geographical distribution than Asia	• Enable the elderly to move about their own, e.g., through the use of self-driving wheel chairs • Associated challenges with short range and long range communication technologies • Resilience mechanism to eliminate the possibility of single point of failure
		Virtual operations with robotic telesurgical systems [64]	2018	The lack of means to tackle the malware programs, that could remotely hijack the robotic software, leading to wrong dissection by remote malicious users No standards are defined or exist for effective haptic (kinesthetic & tactile) feedback	• Network performance (latency, jitter, and packet loss) need to be addressed by Internet 2. • High cost of communication service. • The high end skills of an experienced surgeon, remotely conducting the most complicated tasks in the surgery, are not commonly available
4	Autonomous Vehicles (IoV)	Data driven algorithms for decision making in autonomous vehicles [76]	2018	The lack of verifiability, safety, and explainability in real time, when interacting with many	• Lack of advanced tools for big data acquisition, transmission, storage,

				traffic participants limits the QoS of the algorithms.	and computing for real time decision making
		Autonomous driving system using Q-leraning and previous driving experience [77] Deep reinforcement learning algorithm to control velocity and steering in autonomous vehicles [80]	2016 & 2018	Car Simulator used in controlled environment might overlook some real car control challenges The simulation results showing reduced injury severity might have overlooked the control behaviors in real emergency collisions	• The blackbox problem makes it impossible to test all the unpredictable road scenarios that an autonomous vehile might encounter • Previous driving experience might not cover the future scenarios
5	FinTech	Predicting financial risks to take informed financial decisions using fuzzy multi-agent system. [87]	2012	The used single predictor agent is known to show less accuracy than team agents. The predicted stock data sets are from only two sectors (IT and Airline)	• Physical location of cloud servers, needed for big data accurate prediction, might need compromise on information security and confidentiality
		Constuction of web based Enterprise financial management system detailing financial statistics [90]	2021	Customization of the proposed Enterprise financial management system to the needs of the specific organizations is not addresed	• New tehnology developments in blockchain and cryptography to address the commonplace financial frauds in web based service models
6	Farming	Sensor deployment for collecting crop related data [95 - 101]	2012 - 2017	Unreliable communication with the sensors in harsh environments and rural areas with connectivity issues may lead to signal delay and loss	• Data heterogenity issues - Each sensor has its own data format, temporal characteristics and size. • Lack of tools to predict agriculture yield using data collected from sensors
		Precision agriculture advancements by plant disease detection using convolutional neural networks [104]	2017	The disease detection works for only a pre-established set of diseases stored in the database, as each disease would require an independent training set and time to train on convolutional neural network	• Lack of agricultural strategy, such as crop yields that are adapted to needs, and work schedules that are optimized according to weather forecasts, that could lead to ultra-labor-saving and high-production • Means to enable farm producers to manage production, orders, and inventory in accordance with customer needs
7	Sports & Physical Education	Smart sports equipment embedded with appropriate sensors [111] Wearable sports products with wireless body area network capabilities [109]	2019 & 2021	Consumption of energy and resources, which considerably reduces the duration of the battery. Several limitations: experiments based on dummy (not real players), gravity influence not accounted for, expensive. More data is needed to validate the experimentation	• Short product life cycles, huge energy consumption, absence of standards & scalability to expand using more sensors
		Virtual sports training platforms using augmented reality [113, 115]	2019 & 2020	High equipment price, limited interaction and environmental observations, possible loss of data signal causing connectivity issues	• Limitations of efficient augmented reality technology • Athlete training data storage in cloud platform leading to privacy issues

8	Transportion System	Predicting the traffic congestions for taxi using Neural Networks and Boltzman machine [122] Predicting congestion aware path based on spatiotemporal traffic congestion data [123]	2015 & 2020	Relies on assumptions about adjacent roadway segments to model traffic congestion dynamics, which might be inaccurate. Learning time for Neural Networks makes this approach less viable	• Ways to optimize the travel route taking traffic congestion into account • Widespread usage of fully autonomous driving service with no manual intervension
		Smart train based on data mining algorithms requiring manual intervension [133]	2016	Knowledge from human historical experiences is applied on an experimental platform. More research is needed to apply in real world transportation scenarios.	• Manual intervention is error prone. An autonomous software defined train capable of processing petabytes of data without manual intervention is in its initial stages of development
9	Arts, culture and tourism	Xiaoice [138] a virtual TV anchor and EduRobot [139] an educational chatbot	2014 & 2017	It remains a challenge for Xiaoice to allow more goal-oriented interactions to serve user needs. The reported average accuracy in EduRobot for correct answer is only 63.3%.	• Lack empathetic capabilities, emotional quotient (EQ) and intellectual quotient (IQ)
		Interactive news services chatbot [140]	2021	Limited natural language generation and sentiment analysis capabilities	• Enabling robots as conversation partners to live comfortably on one's own
		Smart travel map based on tourist preferences [141]	2020	The algorithm used (K-Nearest Neighbor) is not suitable for large data sets as it slows down the prediction and increases the computation cost.	• Provide sight seeing routes that match personal preferences and propose optimal plans taking weather and other factors into account
10	Construction	BIM integration with laser scanning, photogrammetry, virtual reality and RFID to improve construction data analyzing efficiency [147]	2020	Focuses on mass-production in Off site Construction Industry (OSC). The lack of OSC industry standards hinders an efficient integration and adoption of these technologies	• Creation of digital twin of the construction structure in cloud platform to analyze the risky construction tasks
		Sensor deployment for construction related parameters collection [148 - 153]	2017 - 2020	Unreliable communication with the sensors in harsh environments and rural areas with connectivity issues may lead to signal delay and loss	• Data heterogenity issues - Lack of common communiction platform

3. Research Challenges and Opportunities

The progress towards the realization of fifth industrial revolution is ubiquitous. Industry 5.0 is expected to make conventional industries smarter by merging machine and human intelligence. This human-machine collaboration would support the workforce by machines taking on mundane tasks like production and manufacturing. The perception-driven and creative side of the work will be open to humans. By realizing this scenario, Industry 5.0 systems will provide humanity with highly accurate automated systems with cognitive skills of human brains. The future high-tech industries where interconnected systems will converge into a single optimal unit, will benefit from the combination of big data analytics, deep learning, internet of things (IoT), cloud computing, augmented reality and cobots. This futuristic single optimal unit will manage information flows between real and cyber world, while integrating computer resources into physical production processes. The interconnected components must integrate heterogeneous communication technologies. Every technology adoption brings its own pros and cons. In Industry 5.0, linking *things* with each other and with *people* has its own set of challenges and opportunities. Industry 5.0 processes would lead to increased productivity, responsive working environment, cost reduction, environment protection and realization of a society where people enjoy a fulfilled life [12]. This would be possible if the associated research challenges are addressed. One such recurring challenge that we witnessed time and again in Section 2 is data driven deep learning mechanisms, for digital twins, that adapt to unpredictable situations. The other identified Industry 5.0 associated challenges needing significant research effort are: novel job requirements, mass personalization, heterogenous data transmission, enhanced efficiency, data security & privacy, and data interoperability. This section identifies the novel research opportunities to address the above-mentioned challenges. The interdisciplinary efforts to address these Industry 5.0 implementation challenges will incorporate cognition in the manufacturing processes, thereby eventually realizing the fifth industrial revolution.

A. Modern work-force:

Industry 5.0 would promote human-machine partnerships by employing systems to eliminate dull, laborious, and repetitive jobs. The examples illustrated in Section 2, such as autonomous cars, AI-assisted crop harvesting, robotic surgeries, machine learning-based painting, 3D construction, driverless drone deliveries, are reshaping the employment structure. This new employment structure leads to the fifth industrial revolution in which human-machine reconciliation would enhance production efficiency. One of the related concerns is that the robots and the artificial intelligence will replace the human factor in workforce [160]. However, this technological unemployment [10] will lead to new and better job opportunities that require creative and innovative thinking. Examples of new roles will be a manager of cobots and automated systems, technology interface designer, artificial intelligence algorithms engineer, smart factory supervisor, staff raising quality and procedures for machines and many more. Facebook has announced recently that the ambitious metaverse augmented reality platform engineering will create 10,000 new jobs in the near future. This demonstrates that Industry 5.0 is about putting humans as the core beneficiary of automation processes. The IoT devices, automated machines and systems will gather and monitor the production and manufacturing data. If the system detects any anomaly in the collected data, a procedure to alert human supervisor will be in place. The human supervisor will decide on the next steps. The software update in automated machines might incorporate certain hard-coded rules or allow the machine learning to evolve for unpredictable situations. Although humanoid robots such as Pepper [161] that recognize and interpret human emotions are already working with the human workforce, programming the ethical and social behavior in machines, such as respect, will be a vital component of human-machine coworking research. Body language interpretation might not be as important as it is in today's workforce. The responsibilities of human resources department will increase with time, as they will be required to manage cobots and machines as well, in addition to humans. The strategy of training enough people to handle these new emerging roles is a research challenge. This adaptation challenge is many-fold. Demir [162] discusses the challenges of integrating robots in the workforce, which are summarized as follows:

- Adaptation of organizational behavior, structures and workflows
- Reception of robots and machines in the working space
- Redefining work ethics such as ambition, repect
- Human Resources department overhauling to encounter prejudice against robots or human workers
- Developing trust parameters in a human-robot collaborative work environment
- Education and training to collaborate with robots
- Redesign of workplace for robotics
- Regulatory concerns regrading accountability when a robot malfunctions

The project MindBot [163] aims to design workplaces where job task difficulty corresponds to the workers' abilities to support worker-cobot interaction in a personalized way. Despite all the progress in AI, humans will remain uniquely qualified for collaborative, creative and custodial tasks in IR 5.0.

B. Mass Personalization:

Industry 5.0 would offer mass personalization instead of mass production. The manufacturers can provide unique solutions to customers that can be enabled by human touch. The integration of human and machine intelligence helps manufacturers to customize products in bulk. Alongside their cobot colleagues, humans would be able to hyper personalize the products with increased speed and accuracy. 3D printing, besides the construction industry, is already in use in other sectors, such as cosmetics, nutrition and health to provide customers with hyper-personalized services. However, their usage is at its very initial stage. L'Oreal uses 3D printing techniques to create customized beauty products. The device Perso prints out customers' favourite lipsticks. The Davinci surgical system [164] is another example of providing personalized precision by using a robotic assistant in surgery procedures. In the future, patients will have customized medicines in hospitals with ultra-personalized chemical and drug contents. However, predicting the effectiveness of products during the mass personalization process is a challenge. A prototype using a digital twin can be created before the manufacturing process. The highly accurate data-driven models of physical objects can be created by using machine learning algorithms. The created prototypes using digital twin and data driven methodology can be used to predict malfunction while improving design and performance. E.g., A prosthetic leg created using 3D printing technology

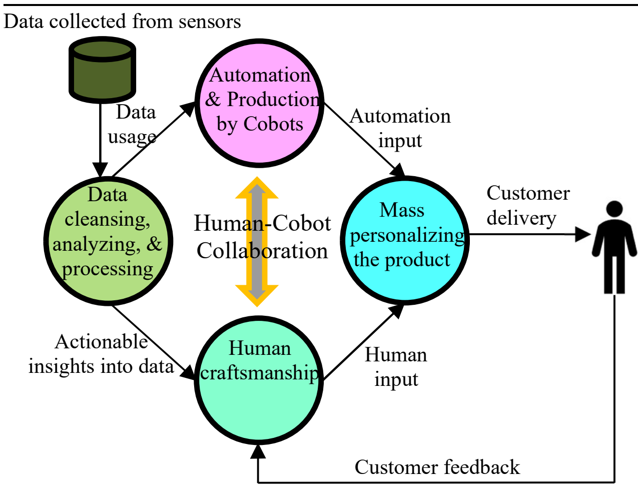

Figure 8. Industry 5.0 compliant smart factory scenario

can be tested and modified with increased precision to meet the personalized needs of a specific patient. During the manufacturing process, the personalized needs might be identified using biological markers such as DNA. Some companies like PlatformE [165] are already using digital twins to tailor a personalized customer experience product. The big brands across all the industries are ready to take their first step to enter the fifth industrial revolution by partnering with such technology companies to develop personalized solutions.

C. *Heterogeneous data transmission:*

Industry 5.0 would involve massive data collection using smart sensors. This collected big data would need quick transfer between different systems, that adhere to multiple communication standards. Each standard uses a unique combination of signals and bands and rely on data interoperability across a diverse range of communication sources. The data transmission across multiple communication standards - including but not limited to - IEEE 802.15.6. ZigBee, WiFi, 5G, and radar remain extremely challenging due to the lack of a common communication platform. This lack of universal standards causes interference while different networks try to coexist. ZigBee operates in the unlicensed 2.4 GHz frequency band and is subjected to interference issues with networks based on IEEE 802.15.6, Bluetooth, and WiFi. Other wireless protocols will be enabled to incorporate ubiquitous connectivity across homes, vehicles, financial institutions, and factories. Although cognitive radio techniques for the coexistence of wireless standards have been around for more than a decade [166], the ever-growing number of signals corresponding to big data, with increasing bandwidths and overlapping bands, adds to this coexistence challenges. As systems become increasingly interconnected, the cyber-physical systems must extend their functionality to integrate heterogeneous communication technologies. This will enable all the systems to work in harmony as a sophisticated single unit.

The initial efforts to design such a solution involves implementing frequency separation or increasing antenna isolation. In the Industry 5.0 framework, these approaches are less viable as they are computationally expensive and require higher energy consumption, thus translating to higher hardware costs. As the usage of the sensors will increase over time, the data transfer approach needs to consider the heterogeneous nature of the collected data. E.g., in a smart factory setting, Cotet [167] sends the encoded data in PNG format to cloud services. The data is collected from smart sensors, actuators, and PLCs. The study is verified on an automated waste collection system.

D. *Enhanced productivity and efficiency:*

The human-machine collaboration will enhance productivity by relieving humans of physically demanding work and focusing on other craftsmanship requiring tasks. The humans will intervene in the machine assigned tasks when the machine requires parameters fine-tuning. In the production process of Rogers Corporation [168], automated software is employed for repetitive tasks, and a camera collects the visual data for the automated tasks. The human worker completes other tasks concurrently and is alerted to adjust the software parameters when the camera finds any visual inconsistencies. This quick turnaround has resulted in an increased production capacity of Rogers Corporation. The new deep learning-based predictive maintenance [169] techniques employ data science and predictive analysis to use the real-time data and generate alerts when care is needed, thereby elevating efficiency. The development of Industry 5.0 predictive maintenance techniques is a promising research area for enhancing productivity and efficiency. Although in their initial stages, robots are available to watch and learn the tedious tasks from their human supervisors. The robots in the manufacturing industry perform a wide variety of manual tasks more efficiently than humans. But Industry 5.0 will witness cobots that work alongside humans in other sectors, such as agriculture, hospitality, logistics and health. FFRobot harvesting robots [91] and IoT-based tractors [170] are increasing production efficiency by many folds in the agriculture sector. Moving towards the productivity enhancement goal of Industry 5.0, it is expected that 40,000 fully automated tractors, not requiring a human operator will be sold in 2038 [171]. As this trend continues, machine adoption will reshape global supply chains by increasing productivity and efficiency.

E. *Security and privacy:*

The industry 5.0 data is massive, heterogeneous, and stored in the cloud computing platforms. The computing algorithms for such heterogeneous big data analysis challenge the traditional encryption methods to ensure security and privacy. The mass personalization of banking, healthcare and transportation services requires people to provide personal data. The lack of personalized data control in clouds makes data susceptible to web-based complexities and legal ramifications. For example, the misleading data security practices resulted in a $ 100,000 penalty [172]. Modern workforce might cause additional security risks. E.g., algorithmic failure of robo-advisors in FinTech might lead to faulty investment advice or online data theft leading to losses of billions of dollars [173]. The development of efficient frameworks using blockchain technologies promises to protect data from unauthorized access and is a hot research spot. The usage of public biometric infrastructure (PBI) to generate biometric signatures would enable users to trust personalized data security. Another security aspect in Industry 5.0 big data paradigm is finding the right trade-off between privacy protection and data analysis. The recent research shows the vulnerabilities arising from adversarial attacks on data analysis machine learning algorithms [174]. The global security and privacy standards such as California Consumer Privacy Act (CCPA) need to be redefined together with new terminologies such as data anonymity. The defined security standards will include new definitions of data anonymity. They will establish guidelines and penalties for Industry 5.0 privacy breach scenarios, such as airspace trespassing by drones with undetected onboard cameras. This will help implement new privacy measures such as: protecting social media data exploitation by third parties for undesired commercial purposes and determining penalties for drone operators contravening those guidelines. Security and privacy incorporation in the personalized services that underpin Industry 5.0 is a research area that needs more attention.

F. Data interoperability:

The Institute of Electrical and Electronics Engineers (IEEE) defines interoperability as “the ability of two or more systems to exchange information and to use the information that has been exchanged” [175]. The diverse Industry 5.0 systems would use wireless sensor networks, cloud computing platforms, cobots, wearable gadgets, autonomous transportation, and drones. This would require a large amount of data integration and interpretation at all levels of CPS to inform production decisions. The main challenge of such Industry 5.0 system deployment is ensuring data interoperability. The Reference Architecture Model for Industry 4.0 (RAMI 4.0) provided an understanding of protocols and standards for data interoperability, but no implementation or application procedures were defined [176]. Semantic interoperability enables systems with multiple standards and services to exchange information with unambiguous meaning. This sematic interoperability can be incorporated by using interoperability providers such as ontologies. An ontology is used to provide a standard for information exchange between different systems [177]. This common standard can facilitate the digital twins’

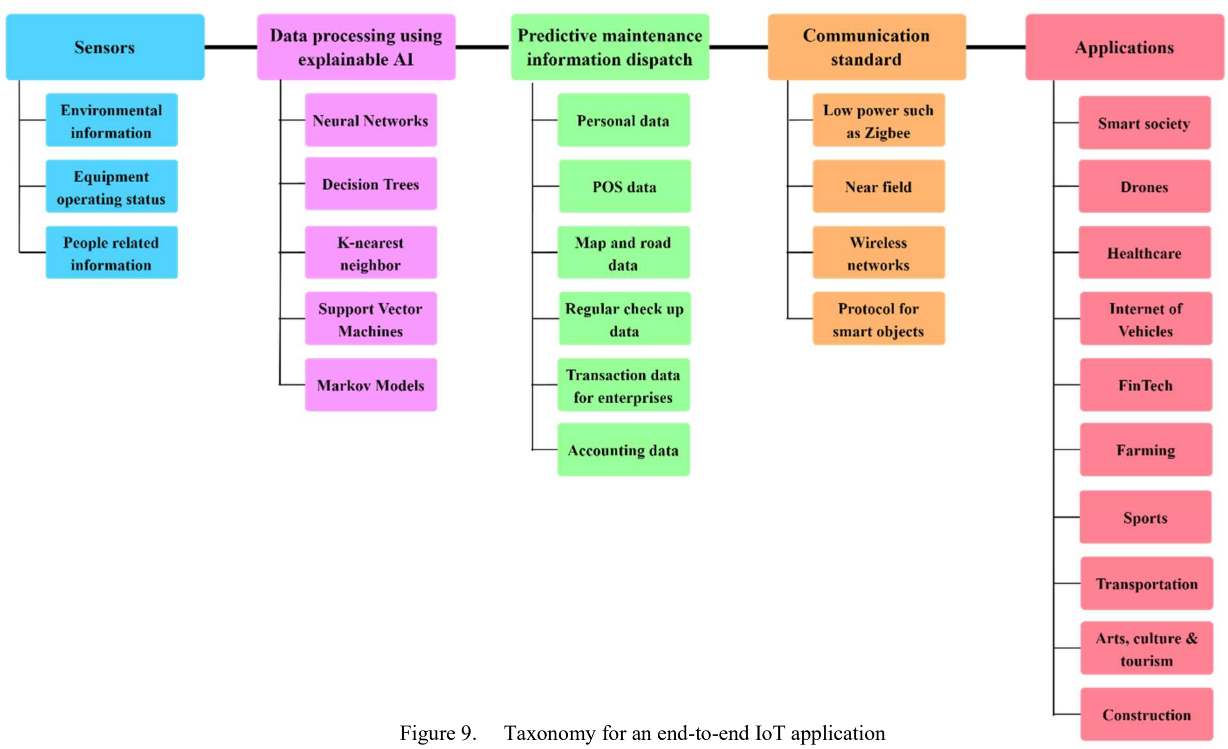

Figure 9. Taxonomy for an end-to-end IoT application

communications that relies on multi-modal and heterogeneous senor data. Madni [178] explains the creation of a reusable top-level ontology that can enable cross domain interoperability in a smart city management where the data is distributed across different organizations and systems [179]. The ontology development to establish interoperability between systems will drive the development of flexible electronic materials such as multi-standard antennas. However, the developed IoT ontologies, so far, are not comprehensive enough to be reused as a basis for the global communication standards for Industry 5.0 interoperable systems [180]. This is because each developed ontology is restricted to a specific domain and a common unified ontology for an end-to-end IoT application, is nonexistent. Further research is needed to understand whether the developed ontologies can be reused as a basis for the global communication standards for Industry 5.0 interoperable systems.

4. DISCUSSION

The fifth industrial revolution will digitize everyday living with human control retaining the centre stage. The notion is that AI will translate big data collected by IoT into a new type of intelligence that will help raise living standards. A few examples include robotic surgeries catering to patients' personal needs, autonomous vehicles alleviating the stress of driving, software defined trains for public transport, transferring cashless money by blockchain technology, and increasing crop production by using smart agriculture techniques. These high-stake scenarios require autonomous systems capable of perceiving, learning, making decisions, and acting independently. Accepting such systems necessitates transparency, which is not accounted for in traditional AI black-box solutions. This lack of clarity could lead to life-threatening consequences, for example, the first autonomous automobile crash led to the operator being charged with negligent homicide [181]. Data scientists currently create explainability metrics and visualizations to monitor these system models on an ad-hoc basis. Moving forward, the big data processing volume will limit human engagement in decision making for these systems, while these algorithmic decisions processing becomes more consequential to the society. This will create a new class of AI algorithms significantly liable to humans about the justification of decisions made. This new class of algorithms will use Explainable AI to overcome the black box problem [81] by justifying the anthropomorphic machine decision. However, the explainability techniques have numerous limitations and lack a universally approved evaluation process among researchers. This is because many explainability techniques rely on linear models to provide only post hoc approximation of the machine learning model's behaviour, which may still misrepresent the nonlinear complex black-box models. The usage of large datasets to address the problem of overfitting is a frequent occurrence for Industry 5.0 applications, further complicating the model, thereby adding to the limitations of the explaining approximations. Moreover, the huge training datasets do not prevent the model from demonstrating shallow performance when confronted with newer scenarios, literally causing loss of lives [181, 182].

TABLE IV: EXPLAINABLE ARTIFICIAL INTELLIGENCE TECHNIQUES WITH ADVANTAGES AND LIMITATIONS

Explanation category	Implementation examples	Advantages	Limitations
Model simplification	Decision trees are used to represent the extracted rules from the Neural Network [183]	The black box processing is explained using easily interpretable models, which results in rules that are simple to comprehend, such as if-else rules	The interpreted models may not well-approximate the original model, as each model has its unique parameters and own set of challenges. The model agnostic explainable models are not mature enough to be employed for incorporating explainability in Industry 5.0 compliant big data applications
	Decision trees and intermediate rules define each hidden layer, which then explains the rules for the following layer [184]		
	Output is analyzed using reverse engineering techniques [185]		
Feature relevance	Neuron wise estimations are used to produce an objective function that explains each neuron signal [186]	The technique functions on an instance-by-instance basis to determine the weight and significance of each parameter in the model's final output. Some implementations provide accurate explanation assurances.	The applications with high correlation among their parameters render this approach less effective. The sensor data for temperature and humidity - collected for Smart Farming or Smart Sports - have high correlation for both the features, rendering this technique counterintuitive. In many circumstances, exact solutions are approximated, resulting in unfavorable spinoff such as the output being influenced by the order of the input variables
	Each neuron's score is backpropagated to create a vector that contains features' importance [187]		
	The activation of neuron is compared to a reference score and the variance is used to calculate the features' importance [188]		

The inherently large data sets for Industry 5.0 applications also introduce other risks such as, increased training time, catastrophic forgetting when training the system with new scenarios, and finding the right compromise between accuracy and explainability. The justification techniques for Industry 5.0 deep learning algorithms, that process big data, fall into one of the two categories: model simplification and feature relevance. Each category has its own set of limitations. E.g., the former [183-185] approximates the rules for each node or neuron during training for subsequent layers. The quality of rule approximation is an important concern in this approach. Furthermore, developing model simplification algorithms gets computationally expensive as the number of layers progressively grow. The feature relevance explanation technique [186-188] addresses this constraint by quantifying a feature's contribution, determining the importance of a specific variable for the overall model. However, this does not correspond to a complete model explanation, and introduces new limitations. We have summarized both the categories in Table IV with their advantages and limitations. Tackling these Explainable AI limitations is yet another research pathway to explore. We also note that choosing the explainability technique depends on the kind of insights user expects to gain. A farmer might need to approximate the rules leading to a drone decision of spraying pesticides. A doctor might need to understand the role of a specific symptom in an automated diagnosis system that has recommended a patient's specific treatment. The explainable AI algorithms have already been used to solve critical problems, such as cancer data classification by analyzing gene expression [189]. However, further research about designing hybrid explainable models that could address the big data predictive maintenance needs for industry 5.0 applications could lead to more significant advances. The sophisticated machines today cannot process the real-world data without converting into standard algorithm labels, which impedes causal analysis and introduces algorithm partiality. In the black-box deep learning algorithms, bias is encountered due to the disproportionate data-set weight of the learnt model, which is attributed to inherent prejudices and deficiencies in the learning algorithm. The public safety case management tool Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) [190] uses a black box model leading to unconscious racial biases in the crime prediction process. Applying human explainable rules for different input data distributions in COMPAS will help understand the skewness in the input training data, eliminating the racial profiling in such critical systems. This will increase the trust and acceptance of such tools, meeting the ultimate goal of Society 5.0, to elevate the quality of life, regardless of region, age, sex, language, race. Further research in this domain will help in developing explainable automated systems that avoid producing biased outcomes, based on race, gender, age or location. Thus, it is critical that the researchers gain new knowledge and create new values by creating AI models that are trusted, transparent, unbiased and justified. DARPA [191], is developing approaches for explaining complex machine learning algorithms. However, progress has been modest in this area. Another related area that needs more attention is the development of new skills in the workforce that could cope with the Industry 5.0 job

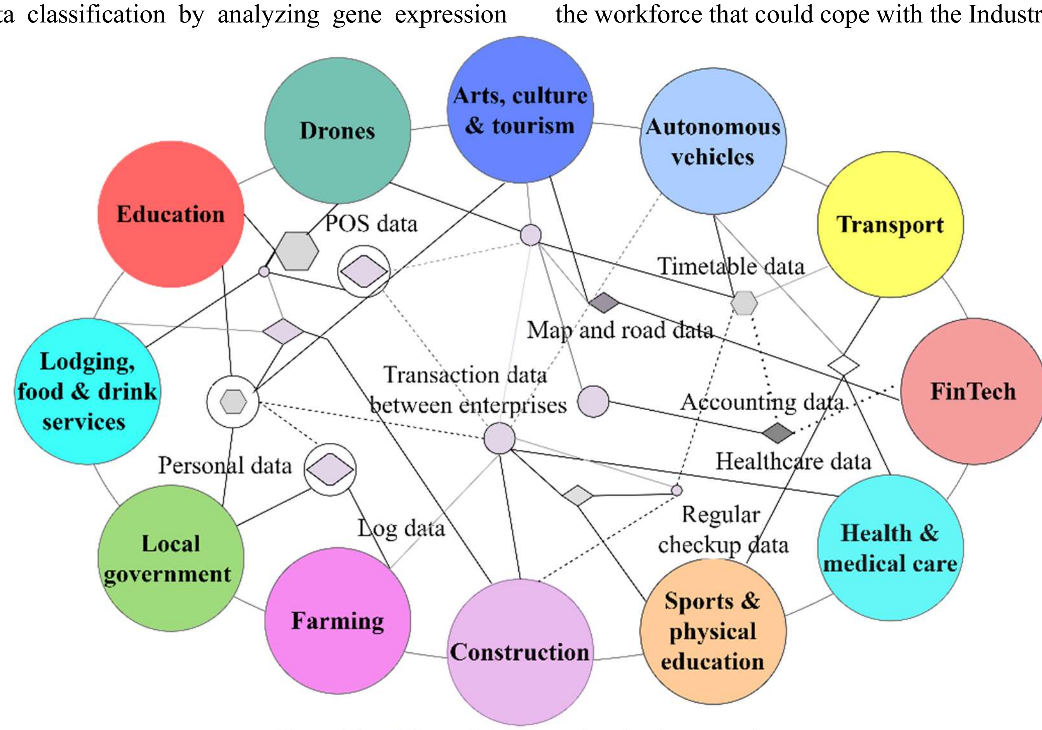

Figure 10. Industry 5.0 connected society by sensor data

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market. According to a Deloitte estimate, there will be 3.4 million jobs available in the next decade, but only 1.4 million competent workers to fill them. To address this challenge, an effort is made in the project BEYOND4.0 [192] that takes full advantage of the digitization opportunities by socially negotiating the technology advancements. This EU project focuses on examining the impact of new technologies on the future of jobs, business models and welfare within the European Union. The Industry 5.0 emphasis is on using big data to improve the service quality that will transform mass production into sustainable mass personalization. This human-centric value puts core human interests at the heart of the production process. Therefore, Industry 5.0 will be a value-driven revolution that would drive the technological transformation to elevate the overall quality of life, for everyone, including the vulnerable populations. To attain this goal of inclusivity, Simões [193] conducts a comprehensive survey of six indoor positioning systems intended for elderly and visually impaired. The indoor positioning systems were grouped in six major categories - radio frequency, inertial sensor, sound, light, computer vision and hybrid - with each category subdivided into multiple subcategories, for evaluation using the criteria of accuracy, coverage, and cost. In a similar but broader scope, this work is an effort to understand the technologies used for social uplift and analyse the gap to reach at Industry 5.0. This article aims at painting a picture of main societal domains to show that technologies such as: wearable smart gadgets, quantum computing based smart contracts, robo-advisors, humanoid robots, data-driven deep learning algorithms, blockchain, cryptographic methods, virtual augmented reality, IoT based tractors, 3Dprinting, high capability sensors, big data processing for cloud platforms at increased rates are already being used. However, certain challenges need to be addressed before the full potential of Industry 5.0 can be realized. Those include effective digital twins creation to predict effectiveness during mass personalization, sensor data communication across multiple standards, predictive maintenance mechanisms to address efficiency needs, secure solutions employing efficient block-chain technologies, standard ontology usage for interoperability, development of standard protocols, and established guidelines for man-machine collaboration. Each of these challenges needs dedicated effort by researchers. Realizing research efforts to address these challenges will open new opportunities leading to a fully autonomous and inclusive society. Such a smart society is defined as: a fully integrated, human-centered, data-driven, equitable society that balances economic advancement with the resolving of social challenges. It is expected to drive next-generation technologies that seamlessly simplify daily life and overcome global problems [12]. The smart society aims to meet the 17 United Nations' Sustainable Development Goals [28]. Besides United Nations, the government policies across the world [194-199] are also encouraging the Industry 5.0. For example; Japan plans to achieve Society 5.0 by facilitating the convergence between cyberspace and physical space; Canada is building policies that favour additive manufacturing and has already seen the 3D printed houses to combat the rising housing prizes; USA has embraced Amazon Go cashierless checkout grocery stores and airport facial recognition programs reflecting modern workforce; The UK has introduced new AI-focused university courses at top universities; France has a billion-dollar AI for humanity plan to enhance economic output, which includes new research facilities, data exchange efforts, and ethical policies; Germany is promoting autonomous driving taxis by introducing new laws; and Singapore is exploring blockchain based digital settlement systems for money transfer. The governments at provincial and local levels are also working to develop far-sighted security policies, drone regulations, and labour laws to protect general public from adverse impacts that might arise as a by-product of the Industry 5.0. All these initiatives ensure prosperity by improving health, education, and overall living standards. The societal domains will be connected via data collected from sensors to form a connected society that would cater to a global community functioning at an elevated level. This will be the fifth industrial revolution

5. Conclusions and Future Directions

Our daily lives are becoming smarter and smoother day by day, because of the technological breakthroughs, attributed to Industrial Revolutions 5.0. In that regard, this work elucidates the possible multidisciplinary approach to actualize the revolution. The identified research opportunities include big data processing by employing machine learning techniques that exploit deep learning and reinforcement learning, AI with explainable approach, drones with multi-domain and application approaches, cognitive based smarter cybersecurity, new generation robotics, additive manufacturing using 3D printing, the Internet of Things in all forms, virtual & augmented reality, blockchain, etc. The in-depth persuasion of these identified directions will multiply the opportunities for the modern workforce, heterogeneous data transmission, enhanced productivity & efficiency, security & privacy measures, and data interoperability. Moreover, this research elaborates the current and uprising research challenges to achieve these goals in the targeted time including, the trained workforce, equipped cybersecurity capabilities for security and privacy, and rapid technology

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adoption. The research community could further work on these identified research challenges and opportunities to address the Industry 5.0 gaps in the near future.

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References

[1] Daniel Paschek & Anca Mocan & Anca Draghici, 2019. "Industry 5.0 – The Expected Impact Of Next Industrial Revolution," Thriving on Future Education, Industry, Business and Society; Proceedings of the MakeLearn and TIIM International Conference 2019

[2] Luckey, Daniel & Fritz, Henrieke & Legatiuk, Dmitrii & Dragos, Kosmas & Smarsly, Kay. (2020). Artificial intelligence techniques for smart city applications.

[3] Internet 2 network https://internet2.edu/ Accessed on: Nov 26, 2021

[4] I.Taj and M.Akil, "'Cognitive Radio Spectrum Evolution Prediction using Artificial Neural Networks based Multivariate Time Series Modelling." The 17th IEEE European Wireless Conference, April, 2011 Austria

[5] Adadi, Amina & Berrada, Mohammed. 2018, "Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence" (XAI). IEEE Access. PP. 1-1. 10.1109/ACCESS.2018.2870052.

[6] Almusaylim, Zahrah & Zaman, Noor. (2019). A review on smart home present state and challenges: linked to context-awareness internet of things (IoT). Wireless Networks. 25. 10.1007/s11276-018-1712-5.

[7] Zaman, Noor & Humayun, Mamoona & Sivanesan, SivaKumar & Masud, Mehedi & Hossain, M. Shamim. (2021). Hybrid smart grid with sustainable energy efficient resources for smart cities. Sustainable Energy Technologies and Assessments. 46. 101211. 10.1016/j.seta.2021.101211

[8] M. Aldabbas, X. Xie, B. Teufel and S. Teufel, "Future Security Challenges for Smart Societies: Overview from Technical and Societal Perspectives," *2020 International Conference on Smart Grid and Clean Energy Technologies (ICSGCE)*, 2020, pp. 103-111, doi: 10.1109/ICSGCE49177.2020.9275630.

[9] George, A. Shaji & George, A. (2020). Industrial Revolution 5.0: The Transformation of the modern manufacturing process to enable man and machine to work hand in hand. Seybold Report. 15. 214-234.

[10] Cobots from Universal Robots www.universal-robots.com Accessed on: Nov 26, 2021

[11] Xu, Li & Xu, Eric & Li, Ling. (2018). Industry 4.0: State of the art and future trends. International Journal of Production Research. 56. 1-22. 10.1080/00207543.2018.1444806.

[12] Mayumi Fukuyama, Society 5.0: Aiming for a New Human-Centered Society, Special Article 2, Japan Economic Foundation, July / August 2018

[13] Lumada: Hitachi Global https://www.hitachi.com/products/it/lumada/global/en/about/index.html Accessed on: Nov 26, 2021

[14] J. Yang, Y. Kwon and D. Kim, "Regional Smart City Development Focus: The South Korean National Strategic Smart City Program," in *IEEE Access*, vol. 9, pp. 7193-7210, 2021, doi: 10.1109/ACCESS.2020.3047139.

[15] Sathish, Prof & Smys, Smys. (2020). A Survey on Internet of Things (IoT) based Smart Systems. Journal of ISMAC. 2. 181-189. 10.36548/jismac.2020.4.001.

[16] Ji Z, Ganchev I, O'Droma M, et al. A cloud-based car parking middleware for IoT-based smart cities: design and implementation. Sensors 2014; 14(12): 22372–22393.

[17] Mulero R, Almeida A, Azkune G, et al. An IoT-aware approach for elderly-friendly cities. IEEE Acc 2018; 6: 7941–7957.

[18] Psomakelis E, Aisopos F, Litke A, et al. "Big IoT and social networking data for smart cities: algorithmic improvements on big data analysis in the context of radical city applications", 2016

[19] Chen N, Chen Y, You Y, et al. Dynamic urban surveillance video stream processing using fog computing. In: Proceedings of the 2nd international conference on multimedia big data (BigMM), Taipei, Taiwan, 20–22 April 2016, pp.105–112. New York: IEEE.

[20] Scuotto, V., Ferraris, A. & Bresciani, S. (2015). Internet of Things: Applications and challenges in smart cities: A case study of IBM smart city projects. Business Process Management Journal. 22(2), 357-367.

[21] Boulos, M.N.K. & Al-Shorbaji, N.M. (2014). On the Internet of Things, smart cities and the WHO healthy cities. International Journal of Health Geographics. 13, 10.

[22] Ding, Yangke & Jin, Mingzhou & Li, Sen & Feng, Dingzhong. (2020). Smart logistics based on the internet of things technology: an overview. International Journal of Logistics Research and Applications. 24. 1-23. 10.1080/13675567.2020.1757053.

[23] Z. Zhou, H. Yu and H. Shi, "Optimization of Wireless Video Surveillance System for Smart Campus Based on Internet of Things," in IEEE Access, vol. 8, pp. 136434-136448, 2020, doi: 10.1109/ACCESS.2020.3011951.

[24] A. C. Şerban and M. D. Lytras, "Artificial Intelligence for Smart Renewable Energy Sector in Europe—Smart Energy Infrastructures for Next Generation Smart Cities," in IEEE Access, vol. 8, pp. 77364-77377, 2020, doi: 10.1109/ACCESS.2020.2990123.

[25] Smart City 2.0 City of Ottawa: Planing, infrastructure and Economic Development https://documents.ottawa.ca/sites/documents/files/smart_city_strategy_en.pdf Accessed on: Mar 14, 2022

[26] Smart City of Toronto Connected Community / Smart City TO – City of Toronto Accessed on: Mar 14, 2022

[27] Seattle Information Technology Strategic Agenda 2017-18 Strategic Agenda - Tech | seattle.gov Accessed on: Mar 14, 2022

[28] The 17 goals for sustainable development https://sdgs.un.org/goals Accessed on: Nov 26, 2021

[29] E. Ahmed, I. Yaqoob, A. Gani, M. Imran and M. Guizani, "Internet-of-things-based smart environments: state of the art, taxonomy, and open research challenges," in *IEEE Wireless Communications*, vol. 23, no. 5, pp. 10-16, October 2016, doi: 10.1109/MWC.2016.7721736.

[30] Anand, S. and M. Anand. "Smart Cities: Environmental Challenges and Green Computing." *International Journal of Advanced Research in Computer Science* 8 (2017): n. pag.

[31] Drone Delivery Canada https://dronedeliverycanada.com/ Accessed on: Nov 26, 2021

[32] Federal Aviation Administration. Unmanned Aircraft Systems Forecast Jan. 2019..https://www.faa.gov/data_research/aviation/aerospace_forecasts/media/Unmanned_Aircraft_Systems.pdf Accessed on: Nov 26, 2021

[33] Integration Pilot Project https://www.faa.gov/uas/programs_partnerships/completed/integration_pilot_program/ Accessed on: Nov 26, 2021

[34] D. Tezza and M. Andujar, "The State-of-the-Art of Human–Drone Interaction: A Survey," in *IEEE Access*, vol. 7, pp. 167438-167454, 2019, doi: 10.1109/ACCESS.2019.2953900.

[35] T. Krajník, V. Vonásek, D. Fiser, and J. Faigl, ``AR-drone as a platform for robotic research and education,'' in *Proc. Int. Conf. Res.*, 2011, pp. 172-186.

[36] Amazon Drones: https://www.amazon.ca/Walkera-Professional-Quadcopter-Transmitter-700TVL/dp/B01AW86EMC Accessed on Dec. 3, 2021

[37] A. Mashood, H. Noura, I. Jawhar, and N. Mohamed, ''A gesture based kinect for quadrotor control,'' in Proc. IEEE Int. Conf. Inf. Commun. Technol. Res. (ICTRC), May 2015, pp. 298–301.

[38] K. LaFleur, K. Cassady, A. Doud, K. Shades, E. Rogin, and B. He, ''Quadcopter control in three-dimensional space using a noninvasive motor imagery-based brain-computer interface,'' J. Neural Eng., vol. 10, no. 4, Aug. 2013, Art. no. 046003.

[39] F. Tepper. University of Florida Held the World's First BrainControlled Drone Race-TechCrunch., 2016 . https://techcrunch.com/2016/04/25/university-of-florida-heldthe-worlds-first-brain-controlled-drone-race/Accessed on: Dec 3, 2021

[40] R. A. S. Fernández, J. L. Sanchez-Lopez, C. Sampedro, H. Bavle, M. Molina, and P. Campoy, ''Natural user interfaces for human-drone multi-modal interaction,'' in Proc. IEEE Int. Conf. Unmanned Aircr. Syst. (ICUAS), Jun. 2016, pp. 1013–1022.

[41] P. Abtahi, D. Y. Zhao, L. E. Jane, and J. A. Landay, ``Drone near me: Exploring touch-based human-drone interaction,'' Proc. ACM Interact., Mobile, Wearable Ubiquitous Technol., vol. 1, no. 3, p. 34, 2017.

[42] G. Jones, N. Berthouze, R. Bielski and S. Julier, "Towards a situated, multimodal interface for multiple UAV control," 2010 IEEE International Conference on Robotics and Automation, 2010, pp. 1739-1744, doi: 10.1109/ROBOT.2010.5509960.

[43] Duan, Xu, Songyun Xie, Xinzhou Xie, Yang Meng and Zhao Xu. "Quadcopter Flight Control Using a Non-invasive Multi-Modal Brain Computer Interface." Frontiers in Neurorobotics 13 (2019): n. pag.

[44] J. R. Cauchard, K. Y. Zhai, and J. A. Landay, ``Drone&me: An exploration into natural human-drone interaction,'' in Proc. ACM Int. Joint Conf. Pervasive Ubiquitous Comput., 2015, pp. 361_365.

[45] J. A. Landay, L. E. Jane, L. E. Ilene, and J. R. Cauchard, ``Drone & Wo: Cultural influences on human-drone interaction techniques,'' in Proc. ACM CHI Conf. Hum. Factors Comput. Syst., 2017, pp. 6794-6799.

[46] He, Debiao & Zeadally, Sherali & Kumar, Neeraj & Lee, Jong-Hyouk. (2016). Anonymous Authentication for Wireless Body Area Networks With Provable Security. IEEE Systems Journal. PP. 1-12. 10.1109/JSYST.2016.2544805.

[47] Kumar, M. & R., Vimala & Britto, K.R.. (2019). A cognitive technology based healthcare monitoring system and medical data transmission. Measurement. 146. 10.1016/j.measurement.2019.03.017.

[48] Weng, Cheng-Hsiung & Huang, Cheng-Kuei & Han, Ruo-Ping. (2016). Disease prediction with different types of neural network classifiers. Telematics and Informatics. 33. 277-292. 10.1016/j.tele.2015.08.006.

[49] Tian, Shuo & Yang, Wenbo & Le Grange, Jehane Michael & Wang, Peng & Huang, Wei & Ye, Zhewei. (2019). Smart healthcare: making medical care more intelligent. Global Health Journal. 3. 10.1016/j.glohj.2019.07.001.

[50] Esteva, Andre & Kuprel, Brett & Novoa, Roberto & Ko, Justin & Swetter, Susan & Blau, Helen & Thrun, Sebastian. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature. 542. 10.1038/nature21056.

[51] Kumar, Adarsh & Krishnamurthi, Rajalakshmi & Nayyar, Anand & Sharma, Kriti & Grover, Vinay & Hossain, Eklas. (2020). A Novel Smart Healthcare Design, Simulation, and Implementation Using Healthcare 4.0 Processes. IEEE Access. 8. 118433-118471. 10.1109/ACCESS.2020.3004790.

[52] Dhanvijay, Mrinai & Patil, Shailaja. (2019). Internet of Things: A Survey of Enabling Technologies in Healthcare and its Applications. Computer Networks. 153. 10.1016/j.comnet.2019.03.006.

[53] Muhammed, Thaha & Mehmood, Rashid & Albeshri, Aiiad & Katib, Iyad. (2018). UbeHealth: A Personalized Ubiquitous Cloud and Edge-Enabled Networked Healthcare System for Smart Cities. IEEE Access. 6. 1-1. 10.1109/ACCESS.2018.2846609.

[54] D. Serpanos, "The Cyber-Physical Systems Revolution," in *Computer*, vol. 51, no. 3, pp. 70-73, March 2018, doi: 10.1109/MC.2018.1731058.

[55] Papa, Armando & Mital, Monika & Pisano, Paola & Giudice, Manlio. (2018). E-health and wellbeing monitoring using smart healthcare devices: An empirical investigation. Technological Forecasting and Social Change. 153. 10.1016/j.techfore.2018.02.018.

[56] Zhu, Hongxu & Wu, Chung & KOO, Cheon & Tsang, Yee & Liu, Yucheng & Chi, Hao & Tsang, Kim-Fung. (2019). Smart Healthcare in the Era of Internet-of-Things. IEEE Consumer Electronics Magazine. 8. 26-30. 10.1109/MCE.2019.2923929.

[57] F. Xiao, Q. Miao, X. Xie, L. Sun, and R. Wang, "Indoor Anti-Collision Alarm System Based on Wearable Internet of Things for Smart Healthcare," IEEE Commun. Mag., vol. 56, no. 4, pp. 53-59, 2018.

[58] M. Chen, Y. Ma, Y. Li, D. Wu, Y. Zhang, and C. H. Youn, "Wearable 2.0: Enabling Human-Cloud Integration in Next Generation Healthcare Systems," IEEE Commun. Mag., vol. 55, no. 1, pp. 54-61, 2017.

[59] Hossain, M. Shamim & Muhammad, Ghulam & Alamri, Atif. (2019). Smart healthcare monitoring: A voice pathology detection paradigm for smart cities. Multimedia Systems. 32. 1-11. 10.1007/s00530-017-0561-x.

[60] D. J. Cook, G. Duncan, G. Sprint and R. L. Fritz, "Using Smart City Technology to Make Healthcare Smarter," in Proceedings of the IEEE, vol. 106, no. 4, pp. 708-722, April 2018, doi: 10.1109/JPROC.2017.2787688.

[61] T. Hilding, "Air quality sensors deployed in U. District Smart City Laboratory,"Washington State Univ. News,2017. https://news.wsu.edu/2017/06/21/u-district-air-sensors/ Accessed on Dec 3, 2021

[62] D. Pal, S. Funilkul, N. Charoenkitkarn and P. Kanthamanon, "Internet-of-Things and Smart Homes for Elderly Healthcare: An End User Perspective," in IEEE Access, vol. 6, pp. 10483-10496, 2018, doi: 10.1109/ACCESS.2018.2808472.

[63] M. Simsek, A. Aijaz, M. Dohler, J. Sachs, and G. Fettweis, "5G-Enabled Tactile Internet," IEEE J. Sel. Areas Commun., vol. 34, no. 3, pp. 460-473, 2016.

[64] Zhang, Qi & Liu, Jianhui & Zhao, Guodong. (2018). Towards 5G Enabled Tactile Robotic Telesurgery.

[65] A. Ahad, M. Tahir and K. -L. A. Yau, "5G-Based Smart Healthcare Network: Architecture, Taxonomy, Challenges and Future Research Directions," in IEEE Access, vol. 7, pp. 100747-100762, 2019, doi: 10.1109/ACCESS.2019.2930628.

[66] K. Guan et al., "5-GHz Obstructed Vehicle-to-Vehicle Channel Characterization for Internet of Intelligent Vehicles," in IEEE Internet of Things Journal, vol. 6, no. 1, pp. 100-110, Feb. 2019, doi: 10.1109/JIOT.2018.2872437.

[67] Kumari, S. & Geethanjali, N.. (2010). A Survey on Shortest Path Routing Algorithms for Public Transport Travel. Global Journal of Computer Science and Technology. 9.

[68] Pinggera, Peter & Ramos, Sebastian & Gehrig, Stefan & Franke, Uwe & Rother, Carsten & Mester, Rudolf. (2016). Lost and Found: detecting small road hazards for self-driving vehicles. 1099-1106. 10.1109/IROS.2016.7759186.

[69] Cheng, Jiujun & Cheng, Junlu & Zhou, Mengchu & Liu, Fuqiang & Gao, Shangce & Liu, Cong. (2015). Routing in Internet of

Vehicles: A Review. IEEE Transactions on Intelligent Transportation Systems. 16. 1-14. 10.1109/TITS.2015.2423667.

[70] Campbell, Sean & O' Mahony, Niall & Krpalkova, Lenka & Riordan, Daniel & Walsh, Joseph & Murphy, Aidan & Ryan, Conor. (2018). Sensor Technology in Autonomous Vehicles : A review. 1-4. 10.1109/ISSC.2018.8585340.

[71] Abboud, Khadige & Omar, Hassan & Zhuang, Weihua. (2016). Interworking of DSRC and Cellular Network Technologies for V2X Communications: A Survey. IEEE Transactions on Vehicular Technology. 65. 1-1. 10.1109/TVT.2016.2591558.

[72] Xu, Wenchao & Zhou, Haibo & Cheng, Nan & Lyu, Feng & Shi, Weisen & Chen, Jiayin & Shen, Xuemin. (2018). Internet of vehicles in big data era. IEEE/CAA Journal of Automatica Sinica. 5. 19-35. 10.1109/JAS.2017.7510736.

[73] Huang, Jian. (2013). Research on Internet of Vehicles and its Application in Intelligent Transportation. Applied Mechanics and Materials. 321-324. 2818-2821. 10.4028/www.scientific.net/AMM.321-324.2818.

[74] Contreras Castillo, Juan & Zeadally, Sherali & Guerrero-Ibañez, Juan. (2017). Internet of Vehicles: Architecture, Protocols, and Security. IEEE Internet of Things Journal. PP. 1-1. 10.1109/JIOT.2017.2690902.

[75] Chen, Min & Tian, Yuanwen & Fortino, Giancarlo & Zhang, Jing & Humar, Iztok. (2018). Cognitive Internet of Vehicles. Computer Communications. 120. 10.1016/j.comcom.2018.02.006.

[76] Schwarting, Wilko & Alonso-Mora, Javier & Rus, Daniela. (2018). Planning and Decision-Making for Autonomous Vehicles. Annual Review of Control, Robotics, and Autonomous Systems. 1. 10.1146/annurev-control-060117-105157.

[77] W. Xia, H. Li and B. Li, "A Control Strategy of Autonomous Vehicles Based on Deep Reinforcement Learning," 2016 9th International Symposium on Computational Intelligence and Design (ISCID), 2016, pp. 198-201, doi: 10.1109/ISCID.2016.2054.

[78] C.J.C.H Watkins and P. Dayan, "Q-learning", Mach Learn, vol.8, nos.3 -4, pp 279-292, 1992

[79] Chae, Hyunmin & Kang, Chang & Kim, ByeoungDo & Kim, Jaekyum & Chung, Chung & Choi, Jun. (2017). Autonomous braking system via deep reinforcement learning. 1-6. 10.1109/ITSC.2017.8317839.

[80] Porav, Horia & Newman, Paul. (2018). Imminent Collision Mitigation with Reinforcement Learning and Vision. 958-964. 10.1109/ITSC.2018.8569222.

[81] Castelvecchi, Davide. (2016). Can we open the black box of AI?. Nature. 538. 20-23. 10.1038/538020a.

[82] Duarte, Fábio & Ratti, Carlo. (2018). The Impact of Autonomous Vehicles on Cities: A Review. Journal of Urban Technology. 25. 1-16. 10.1080/10630732.2018.1493883.

[83] OECD (2018), "Digitalisation and finance: financial markets, insurance and pensions", Organisation for Economic Development and Cooperation, Paris, France

[84] Ferrara, E., Varol, O., Davis, C., Menczer, F. and Flammini, A. (2016), "The rise of social bots", Communications of the ACM, Vol. 59 No. 7, pp. 96-104.

[85] Lee, In & Shin, Yong Jae. (2017). Fintech: Ecosystem, business models, investment decisions, and challenges. Business Horizons. 61. 10.1016/j.bushor.2017.09.003.

[86] Arora, Rashmi. (2018). Financial sector development and smart cities: The Indian Case. Sustainable Cities and Society. 42. 10.1016/j.scs.2018.06.013.

[87] Zarandi, Mohammad & Hadavandi, Esmaeil & Turksen, I.B.. (2012). A hybrid fuzzy intelligent agent-based system for stock price prediction. International Journal of Intelligent Systems. 10.1002/int.21554.

[88] X. Yan and J. Zhao, "Application of Improved Convolution Neural Network in Financial Forecasting," 2019 IEEE 4th International Conference on Cloud Computing and Big Data Analysis (ICCCBDA), 2019, pp. 321-326, doi: 10.1109/ICCCBDA.2019.8725661.

[89] Chen, Dongmei & Xiao, Dan & Li, Yu & Shao, TianLong & Meng, Wei. (2021). Automatic approval method for financial reimbursement of electric power enterprises based on RPA robot. 231-234. 10.1109/CTMCD53128.2021.00056.

[90] L. Yu, "Research on the Construction and Application of Computer Financial Analysis System in Enterprises," 2021 IEEE Asia-Pacific Conference on Image Processing, Electronics and Computers (IPEC), 2021, pp. 411-415, doi: 10.1109/IPEC51340.2021.9421255.

[91] FFRobotics-The future of fresh fruit harvest https://www.ffrobotics.com/ Accessed on: Nov 26, 2021

[92] Farhum, St & Paradhita, Lantun & Ihsan, Yudi. (2020). Utilization of vessel multi aid (VMA) as a smart fishing technology for small scale fisheries. IOP Conference Series: Earth and Environmental Science. 564. 012081. 10.1088/1755-1315/564/1/012081.

[93] K. Benke and B. Tomkins, ``Future food-production systems: Vertical farming and controlled-environment agriculture," *Sustainability, Sci.,Pract. Policy*, vol. 13, no. 1, pp. 13_26, 2017.

[94] Rufí-Salís, Martí & Calvo, Milena & Petit-Boix, Anna & Villalba, Gara & Gabarrell Durany, Xavier. (2020). Exploring nutrient recovery from hydroponics in urban agriculture: An environmental assessment. Resources Conservation and Recycling. 155. 10.1016/j.resconrec.2020.104683.

[95] N. Srivastava, G. Chopra, P. Jain, and B. Khatter, ``Pest monitor and control system using wireless sensor network (with special reference to acoustic device wireless sensor)," in *Proc. 27th Int. Conf. Elect. Electron.Eng.*, Goa, India, Jan. 2013, pp. 1-7.

[96] J. S. Dvorak, M. L. Stone, and K. P. Self, ``Object detection for agricultural and construction environments using an ultrasonic sensor," *J. Agricult. Saf. Health*, vol. 22, no. 2, pp. 107_119, 2016.

[97] F. J. García-Ramos, M. Vidal, A. Boné, H. Malón, and J. Aguirre, ``Analysis of the air _ow generated by an air-assisted sprayer equipped with two axial fans using a 3D sonic anemometer," *Sensors*, vol. 12, no. 6, pp. 7598_7613, 2012.

[98] D. J. Cocovi-Solberg, M. Rosende, and M. Miró, ``Automatic kinetic bioaccessibility assay of lead in soil environments using _ow-through microdialysis as a front end to electrothermal atomic absorption spectrometry," *Environ. Sci. Technol.*, vol. 48, pp. 6282_6290, May 2014.

[99] A. Crabit, F. Colin, J. S. Bailly, H. Ayroles, and F. Garnier, ``Soft water level sensors for characterizing the hydrological behaviour of agricultural catchments," *Sensors*, vol. 11, no. 5, pp. 4656_4673, 2011.

[100] G. Pajares, ``Advances in sensors applied to agriculture and forestry,"*Sensors*, vol. 11, no. 9, pp. 8930_8932, 2011.

[101] J. Gao *et al.*, ``Data-driven forest _re analysis," presented at the Smart-World, Ubiquitous Intell. Comput., Adv. Trusted Comput., Scalable Comput.Commun., Cloud Big Data Comput., Internet People Smart City Innov.(SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI), San Francisco, CA, USA, Aug. 2017. doi: 10.1109/UIC-ATC.2017.8397558.

[102] Akhter, Fowzia & Alahi, Md & Mukhopadhyay, S.C.. (2021). Recent Advancement of the Sensors for Monitoring the Water Quality Parameters in Smart Fisheries Farming. Computers. 10. 1-20. 10.3390/computers10030026.

[103] W. Zou, W. Jing, G. Chen, Y. Lu and H. Song, "A Survey of Big Data Analytics for Smart Forestry," in IEEE Access, vol. 7, pp. 46621-46636, 2019, doi: 10.1109/ACCESS.2019.2907999.

[104] Hanson A, Joel M G, Joy A, Francis J. Plant leaf disease detection using deep learning and convolutional neural network. International Journal of Engineering Science, 2017; 5324.

[105] Sun Y, Zhu L, Wang G, Zhao F. Multi-input convolutional neural network for flower grading. Journal of Electrical and Computer Engineering, 2017; Article ID 9240407, 8p. https://doi.org/10.1155/2017/9240407.

[106] Namin S T, Esmaeilzadeh M, Najafi M, Brown T B, Borevitz J O. Deep phenotyping: Deep learning for temporal phenotype/genotype classification. bioRxiv, 2017.

[107] M. Das and S. K. Ghosh, ``Deep-STEP: A deep learning approach for spatiotemporal prediction of remote sensing data," *IEEE Geosci. Remote Sens. Lett.*, vol. 13, no. 12, pp. 1984_1988, Dec. 2016. doi: 10.1109/LGRS.2016.2619984.

[108] L. Junhong, "Research on Intelligent Development of Sports Product," 2020 International Conference on Artificial Intelligence and Education (ICAIE), 2020, pp. 123-126, doi: 10.1109/ICAIE50891.2020.00036.

[109] I. P. Guembe et al., "Basketball Player On-Body Biophysical and Environmental Parameter Monitoring Based on Wireless Sensor Network Integration," in IEEE Access, vol. 9, pp. 27051-27066, 2021, doi: 10.1109/ACCESS.2021.3054990.

[110] Noitom Motion Capture Systems - MySwingProfessioal https://www.noitom.com/myswing Accessed on: Nov 26, 2021

[111] T. Stone, N. Stone, N. Roy, W. Melton, J. B. Jackson and S. Nelakuditi, "On Smart Soccer Ball as a Head Impact Sensor," in IEEE Transactions on Instrumentation and Measurement, vol. 68, no. 8, pp. 2979-2987, Aug. 2019, doi: 10.1109/TIM.2018.2872307.

[112] Wei, Shiqing & Huang, Puquan & Li, Rui & Liu, Zhiguo & Zou, Yuepei. (2021). Exploring the Application of Artificial Intelligence in Sports Training: A Case Study Approach. Complexity. 2021. 1-8. 10.1155/2021/4658937.

[113] Li Lei, Zhao Fatian, Wang Haiou, New Considerations on Smart Sports and Chinese Martial Art, International Journal of Sports Science and Physical Education. Vol. 4, No. 4, 2019, pp. 45-50. doi: 10.11648/j.ijsspe.20190404.11

[114] Xie, Jun & Chen, Guohua & Liu, Shuang. (2021). Intelligent Badminton Training Robot in Athlete Injury Prevention Under Machine Learning. Frontiers in Neurorobotics. 15. 621196. 10.3389/fnbot.2021.621196.

[115] Lee, H.-S.; Lee, J.-H. The Effect of T-Ball Class on Physical Self-Efficacy of Elementary School Students Using Virtual Reality Technology (VR). Korean J. Sports Sci. 2020, 29, 613–624.

[116] Elite Training QB SIM https://qbsim.com/ Accessed on: Nov 26, 2021

[117] Zhang, Lan. (2020). Design of a sports culture data fusion system based on a data mining algorithm. Personal and Ubiquitous Computing. 24. 10.1007/s00779-019-01273-6.

[118] Wang, Jian & Lv, Bin. (2019). Big data analysis and research on consumption demand of sports fitness leisure activities. Cluster Computing. 22. 10.1007/s10586-018-2207-y.

[119] W. C. Chu, C. Shih, W. Chou, S. I. Ahamed and P. Hsiung, "Artificial Intelligence of Things in Sports Science: Weight Training as an Example," in Computer, vol. 52, no. 11, pp. 52-61, Nov. 2019, doi: 10.1109/MC.2019.2933772.

[120] J. Lopes, J. Bento, E. Huang, C. Antoniou, and M. Ben-Akiva, "Traffic and mobility data collection for real-time applications," in Proc. IEEE Intell. Transp. Syst. (ITSC), Sep. 2010, pp. 216–223.

[121] C. Asensio, J. López, R. Pagán, I. Pavón, and M. Ausejo, "GPSbased speed collection method for road traffic noise mapping," Transp. Res. D, Transp. Environ., vol. 14, no. 5, pp. 360–366, 2009.

[122] X. Ma, H. Yu, Y. Wang, and Y. Wang, "Large-scale transportation network congestion evolution prediction using deep learning theory," PLoS ONE, vol. 10, no. 3, p. e0119044, 2015.

[123] C. Lin, G. Han, J. Du, T. Xu, L. Shu and Z. Lv, "Spatiotemporal Congestion-Aware Path Planning Toward Intelligent Transportation Systems in Software-Defined Smart City IoT," in IEEE Internet of Things Journal, vol. 7, no. 9, pp. 8012-8024, Sept. 2020, doi: 10.1109/JIOT.2020.2994963.

[124] Zheng, Vincent & Wu, Wenbing & Chen, Xin & Hu, Rongxin & Liu, Xin & Wang, Pu. (2017). A Traffic Sensing and Analyzing System Using Social Media Data. ACTA AUTOMATICA SINICA. 44. 10.16383/j.aas.2017.c160537.

[125] Fei-YueWang, "Scanning the Issue and Beyond: Crowdsourcing for Field Transportation Studies and Services." IEEE Trans. Intell. Transp. Syst. 16(1): 1-8 (2015)

[126] J. Xiao and Y. Liu, "Traffic incident detection using multiple-kernel support vector machine," Transp. Res. Rec., J. Transp. Res. Board, pp. 44–52, Dec. 2012.

[127] German Tech Startup 4 Pilots https://4pilots.io/ Accessed on: Nov 26, 2021

[128] Tech Wire Asia https://techwireasia.com/2021/05/baidu-rolls-out-chinas-first-paid-driverless-taxi-service/ Accessed on Dec 21, 2021

[129] I. R. Kamel, H. Abdelgawad, and B. Abdulhai, "Transportation big data simulation platform for the greater toronto area (GTA)," in Smart City 360°. New York, NY, USA: Springer, 2016, pp. 443–454.

[130] S. Kosolsombat and K. Saraubon, "A Review of the Prediction Method for Intelligent Transport System," 2018 18th International Symposium on Communications and Information Technologies (ISCIT), 2018, pp. 237-240, doi: 10.1109/ISCIT.2018.8588015.

[131] Y. Lv, Y. Duan, W. Kang, Z. Li, and F.-Y. Wang, "Traffic flow prediction with big data: A deep learning approach," IEEE Trans. Intell. Transp. Syst., vol. 16, no. 2, pp. 865–873, Apr. 2015.

[132] N. Polson and V. Sokolov. "Deep learning for short-term traffic flow prediction." https://arxiv.org/abs/1604.04527 2016

[133] J. Yin, D. Chen, and Y. Li, "Smart train operation algorithms based on expert knowledge and ensemble CART for the electric locomotive," Knowl.-Based Syst., vol. 92, pp. 78–91, Jan. 2016.

[134] The NewYork Times (newspaper) https://www.nytimes.com/2018/10/25/arts/design/ai-art-sold-christies.html Accessed on: Nov 26, 2021

[135] IBM Research https://www.ibm.com/blogs/think/2016/08/cognitive-movie-trailer/ Accessed on: Nov 26, 2021

[136] Ali Baba Cloud https://www.alibabacloud.com/blog/alibaba-luban-ai-based-graphic-design-tool_594294 Accessed on: Nov 26, 2021

[137] The Verge Newspaper https://www.theverge.com/2017/8/24/16195858/amazon-ai-fashion-designer Accessed on: Nov 26, 2021

[138] Microsoft news https://news.microsoft.com/apac/features/much-more-than-a-chatbot-chinas-xiaoice-mixes-ai-with-emotions-and-wins-over-millions-of-fans/ Accessed on: Nov 26, 2021

[139] Budiharto, Widodo & Cahyani, Anggita & Rumondor, Pingkan & Suhartono, Derwin. (2017). EduRobot: Intelligent Humanoid Robot with Natural Interaction for Education and Entertainment. Procedia Computer Science. 116. 564-570. 10.1016/j.procs.2017.10.064.

[140] S. García-Méndez, F. De Arriba-Pérez, F. J. González-Castaño, J. A. Regueiro-Janeiro and F. Gil-Castiñeira, "Entertainment Chatbot for the Digital Inclusion of Elderly People Without Abstraction Capabilities," in IEEE Access, vol. 9, pp. 75878-75891, 2021, doi: 10.1109/ACCESS.2021.3080837.

[141] I. D. Wahyono, K. Asfani, M. M. Mohamad, A. Aripriharta, A. P. Wibawa and W. Wibisono, "New Smart Map for Tourism using Artificial Intelligence," 2020 10th Electrical Power, Electronics, Communications, Controls and Informatics Seminar (EECCIS), 2020, pp. 213-216, doi: 10.1109/EECCIS49483.2020.9263435.

[142] R. Ramos-Carrasco, S. Galvez-Diaz, V. Nuñez-Ponce and J. Alvarez-Merino, "Artificial neural networks to estimate the forecast of tourism demand in Peru," 2019 IEEE Sciences and Humanities International Research Conference (SHIRCON), 2019, pp. 1-4, doi: 10.1109/SHIRCON48091.2019.9024873.

[143] P. Chen, "Strategy of Artificial Intelligence Assisted Health Tourism in the Perspective of Global Region Based on Markov Chain Model," 2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC), 2020, pp. 391-394, doi: 10.1109/ICCMC48092.2020.ICCMC-00073.

[144] A. LaViers, Y. Chen, C. Belta and M. Egerstedt, "Automatic Sequencing of Ballet Poses," in IEEE Robotics & Automation Magazine, vol. 18, no. 3, pp. 87-95, Sept. 2011, doi: 10.1109/MRA.2011.942118.

[145] Ozcimder, Kayhan & Kong, Zhaodan & Wang, Shuai & Baillieul, John. (2018). Perceiving Artistic Expression: A Formal Exploration of Performance Art Salsa. IEEE Access. PP. 1-1. 10.1109/ACCESS.2018.2871003.

[146] Maskuriy, Raihan & Selamat, Ali & Maresova, Petra & Krejcar, Ondrej & David, Oladipo. (2019). Industry 4.0 for the Construction Industry: Review of Management Perspective. Economies. 7. 14. 10.3390/economies7030068.

[147] Wang, Mudan & Wang, Cynthia & Sepasgozar, Samad & Zlatanova, Sisi. (2020). A Systematic Review of Digital Technology Adoption in Off-Site Construction: Current Status and Future Direction towards Industry 4.0. Buildings. 10.3390/buildings10110204.

[148] Valinejadshoubi, M.; Bagchi, A.; Moselhi, O. Development of a BIM-Based Data Management System for Structural Health Monitoring with Application to Modular Buildings: Case Study. J. Comput. Civ. Eng. 2019, 33, 05019003.

[149] Mao, C.; Tao, X.; Yang, H.; Chen, R.; Liu, G. Real-time carbon emissions monitoring tool for prefabricated construction: An IoT-based system framework. In Proceedings of the 2018 International Conference on Construction and Real Estate Management: Sustainable Construction and Prefabrication (ICCREM 2018), Charleston, SC, USA, 9–10 August 2018; pp. 121–127.

[150] Liu, G.; Yang, H.; Fu, Y.;Mao, C.; Xu, P.; Hong, J.; Li, R. Cyber-physical system-based real-time monitoring and visualization of greenhouse gas emissions of prefabricated construction. J. Clean. Prod. 2020, 246.

[151] Wang, Z.; Hu, H.; Zhou, W. RFID Enabled Knowledge-Based Precast Construction Supply Chain. Comput. Aided Civ. Infrastruct. Eng. 2017, 32, 499–514.

[152] Li, X.; Chi, H.L.;Wu, P.; Shen, G.Q. Smart work packaging-enabled constraint-free path re-planning for tower crane in prefabricated products assembly process. Adv. Eng. Inform. 2020, 43.

[153] Li, X.; Chi, H.L.; Zhang,W.F.; Shen, G.Q. Monitoring and alerting of crane operator fatigue using hybrid deep neural networks in the prefabricated products assembly process. In Proceedings of the 36th International Symposium on Automation and Robotics in Construction (ISARC 2019), Ban_, AB, Canada, 21–24 May 2019; pp. 680–687.

[154] Goh, J.; Hu, S.; Fang, Y. Human-in-the-loop simulation for crane lift planning in modular construction on-site assembly. In Proceedings of the ASCE International Conference on Computing in Civil Engineering 2019: Visualization, Information Modeling, and Simulation (i3CE 2019), Atlanta, GA, USA, 17–19 June 2019; pp. 71–78.

[155] Moon, Sungkon & Ham, Namhyuk & Kim, Sungjin & Hou, Lei & Kim, Ju Hyung & Kim, Jae-Jun. (2020). Fourth industrialization-oriented offsite construction: case study of an application to an irregular commercial building. Engineering, Construction and Architectural Management. ahead-of-print. 10.1108/ECAM-07-2018-0312.

[156] Han, D.; Yin, H.; Qu, M.; Zhu, J.; Wickes, A. Technical Analysis and Comparison of Formwork-Making Methods for Customized Prefabricated Buildings: 3D Printing and Conventional Methods. J. Archit. Eng. 2020, 26.

[157] Smart Bridge by MX3D https://mx3d.com/industries/infrastructure/smart-bridge/ Accessed on: Nov 26, 2021

[158] Carra, Guglielmo & Argiolas, Alfredo & Bellissima, Alessandro & Niccolini, Marta & Ragaglia, Matteo. (2018). Robotics in the Construction Industry: State of the Art and Future Opportunities. 10.22260/ISARC2018/0121.

[159] Kanan, Riad & Elhassan, Obaidallah & Bensalem, Rofaida. (2018). An IoT-based autonomous system for workers' safety in construction sites with real-time alarming, monitoring, and positioning strategies. Automation in Construction. 88. 73-86. 10.1016/j.autcon.2017.12.033.

[160] E. İşcan , "An Old Problem in the New Era: Effects of Artificial Intelligence to Unemployment on the Way to Industry 5.0", Yaşar Üniversitesi E-Dergisi, vol. 16, no. 61, pp. 77-94, Jan. 2021, doi:10.19168/jyasar.781167

[161] Softbank Robotics https://www.softbankrobotics.com/emea/en/pepper Accessed on: Nov 26, 2021

[162] Demir, Kadir & Doven, Gozde & Sezen, Bulent. (2019). Industry 5.0 and Human-Robot Co-working. Procedia Computer Science. 158. 688-695. 10.1016/j.procs.2019.09.104.

[163] Homepage of Mind Bot https://www.mindbot.eu/ Accessed on: Nov 26, 2021

[164] DaVinci surgery: Robotic Assisted Surgery for patients https://www.davincisurgery.com/ Accessed on Dec 21, 2021

[165] PlatfromE – Fashion's form for Mass Customization https://www.platforme.com/ Accessed on: Nov 26, 2021

[166] I.Taj, M.Akil and Hammami, Standard Recognizing Self Organizing Map based Cognitive Radio Transceiver, The 5th IEEE International Conference on Cognitive Radio Oriented Wireless Networks and Communications, 2010, Cannes, France

[167] C.E.Cotet, G.C. Deac, C.N. Deac, C.L. Popa, An Innovative Industry 4.0 Cloud Data Transfer Method for an Automated Waste Collection System. *Sustainability* vol 12. No.5. p 1839, 2020

[168] Rogers Corporation https://www.rogerscorp.com/ Accessed on: Nov 26, 2021

[169] C. Liu, D. Tang, H. Zhu and Q. Nie, "A Novel Predictive Maintenance Method Based on Deep Adversarial Learning in the Intelligent Manufacturing System," in IEEE Access, vol. 9, pp. 49557-49575, 2021, doi: 10.1109/ACCESS.2021.3069256.

[170] Internet Of Business: https://internetofbusiness.com/john-deere-turns-iot-smart-farming/ Accessed on Dec. 3, 2021

[171] Agricultural Robots and Droes to become a 45 billion dollar industry by 2038 https://www.gim-international.com/content/news/agricultural-robots-and-drones-to-become-a-45-billion-dollar-industry-by-2038 Accessed on: Nov 26, 2021

[172] Consumer Finance https://files.consumerfinance.gov/f/201603_cfpb_consent-order-dwolla-inc.pdf Accessed on: Nov 26, 2021

[173] Issues Allen and Overy https://allenovery.com/publications/en-gb/Fintech/Pages/Issues.aspx Accessed on: Nov 26, 2021

[174] Slack, Dylan & Hilgard, Sophie & Jia, Emily & Singh, Sameer & Lakkaraju, Hima. (2020). Fooling LIME and SHAP: Adversarial Attacks on Post hoc Explanation Methods. 180-186. 10.1145/3375627.3375830.

[175] IEEE, "IEEE Standard Computer Dictionary: A Compilation of IEEE Standard Computer Glossaries," *IEEE Std 610,* 1991.

[176] ZVEI (2015). Reference Architecture Model Industrie 4.0 (RAMI 4.0)

https://www.zvei.org/fileadmin/user_upload/Themen/Industrie_4.0/Das_Referenzarchitekturmodell_RAMI_4.0_und_die_Industrie_4.0-Komponente/pdf/5305_Publikation_GMA_Status_Report_ZVEI_Reference_Architecture_Model.pdf Accessed on: Nov 26, 2021

[177] Xu W., Cui J., Li L., Yao B., Tian S., Zhou Z. Digital twin-based industrial cloud robotics: Framework, control approach and implementation. Journal of Manufacturing Systems. 2021; 58: 196–209. Available at: DOI:10.1016/j.jmsy.2020.07.013

[178] Madni AM., Architecting S., Program E. MBSE Testbed for Rapid, Cost-Effective Prototyping and Evaluation of System Modeling Approaches. 2021; Available at: DOI:10.3390/app11052321

[179] Petrova-Antonova D., Ilieva S. Digital twin modeling of smart cities. Advances in Intelligent Systems andComputing. Springer; 2021; 1253 AISC: 384–390. Available at: DOI:10.1007/978-3-030-55307-4_58

[180] Bajaj, Garvita & Agarwal, Rachit & Singh, Pushpendra & Georgantas, Nikolaos & Issarny, Valérie. (2017). A study of existing Ontologies in the IoT-domain.

[181] The National Transportation Safety Board, "Collision Between Vehicle Controlled by Developmental Automated Driving System and Pedestrian" Accident Report NTSB/HAR-19/03 PB2019-101402, Tempe, Arizona, 2018 https://www.ntsb.gov/investigations/AccidentReports/Reports/HAR1903.pdf Accessed on Mar.14, 2022

[182] Jeremy Petch, Shuang Di, Walter Nelson, "Opening the Black Box: The Promise and Limitations of Explainable Machine Learning in Cardiology", Canadian Journal of Cardiology",Volume 38, Issue 2,2022, Pages 204-213, ISSN 0828-282X, https://doi.org/10.1016/j.cjca.2021.09.004.

[183] M. Sato and H. Tsukimoto, "Rule extraction from neural networks via decision tree induction," IJCNN'01. International Joint Conference on Neural Networks. Proceedings (Cat. No.01CH37222), 2001, pp. 1870-1875 vol.3, doi: 10.1109/IJCNN.2001.938448.

[184] Zilke, Jan & Mencía, Eneldo & Janssen, Frederik. (2016). DeepRED – Rule Extraction from Deep Neural Networks. 457-473. 10.1007/978-3-319-46307-0_29.

[185] Augasta, M.Gethsiyal & Kathirvalavakumar, T.. (2011). Reverse Engineering the Neural Networks for Rule Extraction in Classification Problems. Neural Processing Letters. 10.1007/s11063-011-9207-8.

[186] Kindermans, Pieter-Jan & Schütt, Kristof & Alber, Maximilian & Müller, Klaus-Robert & Erhan, Dumitru & Kim, Been & Dähne, Sven. (2017). Learning how to explain neural networks: PatternNet and PatternAttribution.

[187] Montavon, Grégoire & Lapuschkin, Sebastian & Binder, Alexander & Samek, Wojciech & Müller, Klaus-Robert. (2017). Explaining NonLinear Classification Decisions with Deep Taylor Decomposition. Pattern Recognition. 65. 211–222. 10.1016/j.patcog.2016.11.008.

[188] Shrikumar, Avanti & Greenside, Peyton & Shcherbina, Anna & Kundaje, Anshul. (2016). Not Just a Black Box: Learning Important Features Through Propagating Activation Differences.

[189] Ludwig, Simone & Picek, Stjepan & Jakobovic, Domagoj. (2018). Classification of Cancer Data: Analyzing Gene Expression Data Using a Fuzzy Decision Tree Algorithm. 10.1007/978-3-319-65455-3_13.

[190] Ed Yong, A Popular Algorithm Is No Better at Predicting Crimes Than Random People, The Atlantic, 2018 https://www.theatlantic.com/technology/archive/2018/01/equivant-compas-algorithm/550646/ Accessed on: Nov 26, 2021

[191] Defence Advanced Research Projects Agency https://www.darpa.mil/ Accessed on: Nov 26, 2021

[192] Homepage of Project Beyond4-0 EU https://beyond4-0.eu/ Accessed on: Nov 26, 2021

[193] Simões, Walter & Machado, Guido & Sales, André & Lucena, Mateus & Jazdi, Nasser & Lucena Jr, Vicente. (2020). A Review of Technologies and Techniques for Indoor Navigation Systems for the Visually Impaired. Sensors. 20. 3935. 10.3390/s20143935.

[194] Carin Holroyd (2020): Technologival innovation and building a 'super smart' society: Japan's vision of Society 5.0, Journal of Asian Public Policy, DOI: 10.1080/17516234.2020.1749340

[195] Herron, C.; Ivus, M.; Kotak, Just Press 'Print': Canada's Additive Manufacturing Ecosystem," Information and Communications Technology Council (ICTC), March 2021, Ottawa, Canada.

[196] Your face is, or will be, your boarding pass, NewYork Times https://www.nytimes.com/2021/12/07/travel/biometrics-airports-security.html_ Accessed on Mar.14, 2022

[197] French Strategy for Artificial Intelligence https://www.aiforhumanity.fr/ Accessed on Mar. 14, 2022

[198] Germany gives greenlight to driverless vehicles on public roads TechCrunch 2021 https://techcrunch.com/2021/05/24/germany-gives-greenlight-to-driverless-vehicles-on-public-roads/ Accessed on Mar. 14, 2022

[199] Monetary Authority of Singapore, July 2021 https://www.mas.gov.sg/news/media-releases/2021/monetary-authority-of-singapore-and-banque-de-france-break-new-ground-in-cbdc-experimentation Accessed on Mar. 14, 2022

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