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Research Article

Revolutionizing Engine Manufacturing: IoT-Driven Heartbeat Monitoring with Agentic AI Innovations

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ABSTRACT

The heartbeat sensor includes photoplethysmography (PPG) technology that can detect the heart rate optically. The architecture will do the data processing and machine learning model inference to predict the heart rate. The general block diagram is to have the sensor collecting data and a microcontroller board doing pre-processing capabilities, such as FFT. A host computer will run the machine learning model so all the Interpretation can be python scripts uploaded to the microcontroller board.

AMED is a health, care, and welfare R&D organization that has been tasked by the Japanese government to support its national strategies while promoting research toward addressing highly social needs. It is also the Ministry of Health, Labor, and Welfare that has been the central government of the comprehensive health and welfare field in Japan. Since 2000, an average of 20% of the national annual budget has been appropriated to Japan's health and welfare fields. The overall target of the national strategy, as stipulated in a policy document created by the form of council, are as follows. Higher value-added industries stimulate the economy and improve Japan's international competitiveness. Medical care reform promoting preventive measures for health and welfare problems. High-quality services raise Japan's attractiveness.

Keywords: Nanomaterial, Solid Lubricant Coating, Micromilling, Wear Factor, SEM,IoT (Internet of Things),Engine manufacturing,Heartbeat monitoring,Agentic AI,Predictive maintenance,Smart sensors,Industrial IoT (IIoT),Real-time data analytics,Autonomous systems,AI-powered monitoring,Machine learning algorithms,Predictive analytics,Condition-based monitoring,Engine health optimization,Digital twin technology.

1. INTRODUCTION

Manufacturing processes have not only been a cornerstone of global economies, but they have also profoundly influenced virtually every aspect of people's daily life. Though technologies have advanced by leaps and bounces, due to the fundamental difference in the operation and materials used, the manufacturing industry has continued to rely on the ancient tool and techniques – casting, milling, turning, punching, extruding, forging, stamping, aging, welding and the like – mostly derived from century-old craftsmanship. The epic of successive industrial revolutions is bearing witness to the maturation of a promising suite of novel technologies: Industrial 4.0, internet-of-things, mixed-reality, 3D printing, robotics and AI. With these powerful means, the newly envisioned manufacturing paradigm has the potential to revolutionize this age-old industry completely. Yet a critical enabler would be tools that enable seamless design and deployment of smart devices, a novel item appears to have immediately changed the essence of the production line forever.

Geo-fencing of these devices can illuminate the traffic trajectory of workers inside the facility. On the consideration that the work of manufacturing involves sequential fabrication, painting, inspection, delivering, if one may classify the traffic inside the facility – "traffic" being metaphorically referred to the motion of workers and materials performing those works – an astute observer would easily uncover the activities those workers are engaged in at different locations and different times. This potentially means the activities surrounded by a facility-wide geo-fencing can be spatio-temporally recorded. Not only the activities, most of the times manufacturing also has certain operational workflows – which machines should be used in which order and how, how many cycles each machine should operate before jumping to the next, in case of production lines, which machine would hand over its product to the next machine upon completion and what would be done if a machine were unable to continue processing even in the middle, etc. With the astonishing capability of deep learning, the sequence of the activities, together with their geo-tagged.

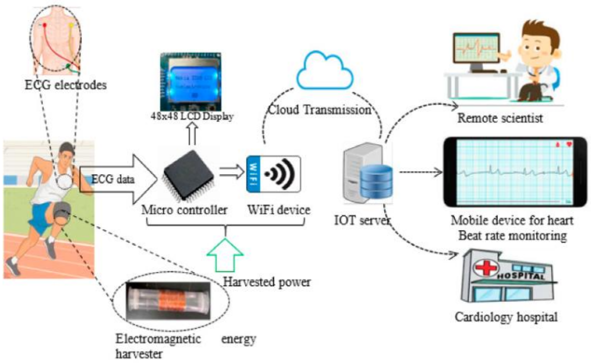

Fig 1: Heartbeat Rate-Monitoring

1.1. Background and Significance Present manufacturing enterprises are preparing to revolutionize typical engine manufacturing processes by applying IoT-driven heartbeat monitoring technology. A highly sensitive piezoelectric film would be utilized to capture micro-vibrations as the heartbeat signal, remoulding a cylinder block. To initiate sample use, a design of the cylinder block composed of sensitive and reference sensing units is to be showcased. Based on empirical test results, learned models alongside the agentic AI innovation scheme have been formulated to optimize the dimensions for micropillaring. As manufacturing excels with more robotization and innovation, intelligent engines equipped with the IoT heartbeat monitoring mechanism are foreseen. Throughout the entire history of industry, innovatory technologies and re-engineering practices have generated great changes in machining products and processes. With contemporary increasing IoT technologies, Internet-connected devices and advanced AI algorithms are encouraging the profound revolution of the manufacturing sector. A sophisticated development of AI-assisted agent networks may allow workers' engagement in maintaining tasks and optimizing maintenance topics for advanced manufacturing devices. Mass production of the cylinder blocks demands an innovative manufacturing scheme and updated machinery, which will additionally lead to varying engine designs. To enhance productivity and intensification in the current tough competition market, firms are shifting focus towards numerical control machinery and the semi-automated/full-automated working shop. With the demands of both high-quality machining and delivery, finishing products are examined at minor nodes using special schemes.

Equ 1: IoT Heartbeat Monitoring Equation

$$H(t) = \alpha \cdot \Delta P(t) + \beta \cdot \Delta T(t) + \gamma \cdot \Delta V(t)$$

Let:

- $\Delta P(t)$ = Pressure change in engine over time t
- $\Delta T(t)$ = Temperature change in engine over time t
- $\Delta V(t)$ = Vibration changes in engine over time t

1.2. Research Objectives In the midst of IR4.0, the world is rapidly working towards a completely new model of manufacturing. Driven by Industry 4.0 and fully integrated data, the intelligent factory mission is to supply consumers with custom, on-demand commodities. In the intelligent factory model, production, logistics, and equipment are digitally attached into a single system so they may observe and evaluate performance based on many sources of information. The mission of scientists and manufacturers is to design, experiment, deploy, and maintain various AI calculations that operate in this rapidly altering environment. Using these AI estimates effectively to control and improve this complex system is an equally difficult job. All unaccounted variations may mean the difference between failure of equipment and maintenance that was not necessary on a factory floor.

The rapid development of Industry 4.0 supplies both a challenge and an opportunity for factories. As older, simpler factories get outcompeted and replaced by factories that are more precise and agile, a threat grows. Nevertheless, Industry 4.0 is taking away the barrier to market entry by allowing more and more diverse business versions. Smaller producers have the benefit of a quickly shifting market to identify gaps and niches. A small-scale producer may supply a sole designer with a certain product, or satisfy the need of a localized town with a particular part for a vehicle. The goal is to have the equipment in your factory to be able to efficiently reconfigure to a completely different product when the opportunity emerges. This objective may not be achievable in the standard Operator-on-the-Loop training flow. Recruiting a skilled engineer with years of experience and knowledge about the equipment may be too expensive for small-scale producers. Moreover, the engineer's solution may be overly concentrated and thus very constrained in succeeding other factory environments. This is the call for a new breed of scalable, general AI that may be taught and deployed easily for a variety of devices. Nowhere is this call more exciting than in the low-cost adoption of Industry 4.0 systems for small- and medium-sized manufacturers (500 to 5,000 employees).

2. IOT IN ENGINE MANUFACTURING

Today in engine manufacturing, implementations of adaptive and autonomous operations are essential to keep up with market requirements on reduced costs, energy saving, waste reduction and short lead times. The machinery industry is the backbone of multiple industries, such as automobile or aeronautics. Producing advanced manufacturing equipment represents an important market in the early 20th century and has continued to expand. Over the past two decades, however, this market has been reduced by market changes. While the rise of new markets creates opportunities for purchasers, it also creates threats in competition for other manufacturers. The number of machinery manufacturers has dropped, affected by market dynamics. This encompasses the aerospace and electrical sectors, with a prolonged spillover impact on other industries. What's more, the unspecific global downturn has caused machinery companies in Europe to retract.

With the advent of Industry 4.0, the Internet of Things (IoT) has been extended to the Industry of Things (IIoT) within the manufacturing context. In the IIoT framework, sensors monitor the machine health in real-time and share the status with each other. While being part of the distributed manufacturing system, it harmonizes the system operating states. IoT has been widely used in the manufacturing domain as a backbone of IIoT systems for predictive maintenance or for further enhancement of part quality. However, the agentic implementation for maintaining the health of manufacturing systems does not exist. 'Agentic' is to develop a tool for utilizing the individual manufacturing machines as an agent for handling the machinery condition parameters.

The technical contribution of this study is twofold:

1. Engine manufacturing line is modeled as a set of individual Cyber-Physical Production Systems (CPPSs) which can be used as an implementation environment of a monitoring system.

2. To maintain the health of the production line, a novel methodology, namely 'Agentic AI', is introduced. Industrial machining data is processed in the agent for the whole middleware system and the agent is in charge to take the response for the health of the shop floor.

2.1. IoT Applications in Manufacturing Manufacturing is the main driver of the global economy, and it is anticipated that technological advances such as the Internet of Things (IoT), Expanded Reality (XR) technology, and public-generally containing businesses could impact manufacturing in a significant way starting in the early 2020s. This paper highlights recent advances in XR technology and AI-supported IoT systems for monitoring connected machines. This innovative approach juxtaposes dedicated gadgets with generally accessible AI models provided by technology companies. To respond to marketplace fragmentation, the notion of agentic AI is articulated and associated to a specific conclusion. The main contribution is a parametric model of the agentic AI marketplace which is applied to conclude that industry consolidation efforts are likely to a certain cost. This consolidation might increase environmental injustice concerns, while also lowering the budget prerequisites for adopting smart-factory practices. This indicates that, without feedback monitoring, industry incumbents could paradoxically hamper broad societal IoT benefits.

Manufacturing is a significant driver of the economy. In 2019, the sector accounted for 26.98% of the worldwide Gross Domestic Product. The crisis resulting from the spread of Covid-19 revealed the significance of this sector, highlighted through appreciation of its pivotal role in achieving the resilience of nation states. The first industrial revolution was driven by the introduction of mechanisation, the second experiment focused on mass production and harnessing electricity, and the third one brought about computerisation. The fourth industrial revolution was powered by Internet connectivity and using it to structure Connected Things. In China's long-term development proposal, the technological divergence from the primary model of the economy is emphasised. The country is targeting high-quality growth, with an increased emphasis on a consumer-oriented economy, improvements to the environment, and efforts to bolster change. A series of conjunctural motives suggest that linked investments in manufacturing with IoT and AI are both viably promising and to be expected.

Fig 2: Industrial Applications for Smart Manufacturing

2.2. Benefits and Challenges A stable heartbeat supports the life of people. Similarly, ensuring that a plant or a building operates stably can dramatically improve the quality of services provided. People monitor the condition of their body through regular heartbeat testing. By monitoring the "heartbeat" of the machines, it is anticipated that the lifespan of equipment can be largely extended. Additionally, efficient maintenance, exploiting real-time equipment data, will reduce downtime. These days, the Industrial Internet of Things technologies have been widely adopted in the manufacturing industry. Many sensor devices are attached to industrial equipment; equipment data are automatically collected that informs machine conditions. While data volume rapidly increases, key data that indicate the equipment condition are likely hidden. Inspired by the fact that the acoustical sound of a heartbeat often carries feelings of comfort and love, an agentic-like AI heartbeat model is invented that enables an intuitive, at-a-glance understanding of frequently changing or hidden trends in equipment data. Considerable benefits can be expected to greatly outweigh the initial cost. With the help of edge-to-cloud IIoT and the AI heartbeat model, a path to revolutionize engine manufacturing was developed. Revolutionizing engine manufacturing comprises two key pillars. A number of agents keep monitoring the plant heartbeat through real-time engine data. The heartbeat data give workers and managers an intuitive grasp of the operational state of the plant. In case of an unexpected state, the agents generate notifications. These contain conjectures about potential problems, their predicted seriousness, and countermeasure suggestions. The AI heartbeat model enables an intuitive understanding of "hidden" changes in the plant by hearing the heartbeat of the agents.

3. HEARTBEAT MONITORING IN ENGINE MANUFACTURING

The 10th St. Gallen International Symposium will be held at the University of St. Gallen on 18th August 2022. Sixty years ago in this context, Friedrich Dürrenmatt wrote: "The shock began to abate only, then it turned into anger, a blind rage growing more intense as it became more futile." Symptomatic of the same latitudes, have people not been feeling exactly the same way about the way automation has revolutionized manufacturing? On the one hand, heartbeats were always there, unmonitored – one of the most prominent industries of the Swiss region being spared of what for most has been an inexorable terror. On the other hand, this paranoia is obsolete, "one of the most pernicious vexations that have troubled the Swiss Confederation since time began..." – implemented with the frantic tempo of models rolling on belts, turning apparition into premonition. These are the stakes then: placing a white factory with oracles that do not shackle to the shield.

The celebration of the revolutionary impact of the fourth industrial revolution is met by a particular resonance where spindle automation casts its long shadow. How much more staggering this transformation of the industrial environment, then – traversing the always-pending penetration of the Internet of Things – with its extension to the industrial sphere? Blanket all with chips: the incessant renewal of the so-called "computer protocols" puts the last screws to what is uniform a straitjacket of ontological stasis and amorphous unsealment. Just as machines have a heart, EKG pads pocked underneath the armor-like casing pound and wheeze information bubbles of despair. What is peculiar to the asea odor of the coffee? Haruspex to the divination! May there not be ledgers that pace to their doom? Let the future sweat from the transpirated pulse of horloges. But what can a heart know, such that it is none other than tick and tock? That it conforms to the chemistry of the occasion – what else? Fixed be then the remembrance of that tock – awaken not the beasts that cluster the belt. So then, is nothing dead?

A basic characteristic of smart manufacturing is the ability to digitally capture and evaluate the operational status of equipment, operating resources and structures; analysts are then enabled to draw appropriate conclusions. This production methodological engine operates in accordance with a previously created plan of instruction. Basic to these plans – well in advance – remained the specification of which equipment in which order shall be involved in the machining processes, which tools might accomplish an operation and what parameters generate an acceptable result. All these setups compose what is conventionally denominated, and almost systematically left to the safe box of plant managers' archive, engineering standards. Working in a spatial network of extremely sophisticated machines, happily cajoled by there-of even more sophisticated operators, in the exact determination of action-object pair, aggression-behavior couple, conjuncture-functionality pair, well all of thereof; such is the goal of the proposed approach. By designing equipment as agents, the unchallenged authority vested in them by the finality of the production modes opens a breach to a world of teleological forwarding yet locked to the irremediable error of instance.

3.1. Importance of Heartbeat Monitoring The heartbeat is one of the most important indicators of the body's health condition. It can be influenced by different diseases due to the different impact that the cardiac function causes, leading to health risks. Thus, data concerning heartbeat plays a significant role in the research and diagnosis of various diseases. The heartbeat test has been accepted as a common examination in hospitals around the world. To make it more accurate, users should keep completely relaxed, still, and silent, for they may be allowed not to even breathe.

In recent years, with the development of Internet of Things (IoT) technologies, wearable heartbeat devices have been popular. These small devices can measure the heartbeat data more frequently compared with traditional hospital equipment. The daily heartbeat curve can be collected all the time and analyzed, discovering health risks much earlier than they will show up. However, even if one is wearing a heartbeat bracelet all day long, the device still needs to be requested deliberately to stop movement to make the reading accurate. This is a large limitation for real applications, because a part of the heartbeat data could be invaluable if the user has an unstable lifestyle. In this paper, the author presents how the partial least square regression (PLSR) method is used to build the mapping between the noisy and noiseless heartbeat dataset. In this way, the heartbeat data can be collected continuously during the daily activities, and any sensible devices will send warnings as soon as health risks are detected. An agentic artificial intelligent (AI) learning model is trained based on geographic location data corresponding to orthostatic position changes.

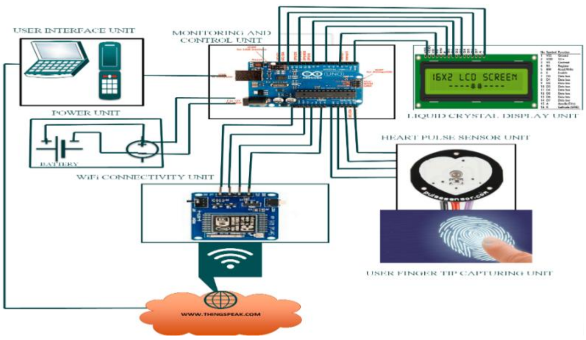

Fig 3: Human Heartbeat Rate Monitoring

3.2. Existing Technologies and Limitations There are already several implementations that tackle gauge/pointer interaction: uses analytic transformation to align the object of interest and through this, creates a region where the gauge needle can be detected. Then it proposes that the gauge will be positioned in an area such that it covers the main brain lobe. Another implementation also relies on a region where the gauge/contact is expected, and the gauge position is detected via a marker. However, designing such a marker can be onerous, and the gauge used in the image acquisition was specifically designed for a reference test bench.

When an industrial environment is considered, the gauge analogue characteristics impose that the gauge transparent window covering the brain is narrow, thus cannot guarantee that marker detection could be feasible. Instead, image processing should monitor the entire gauge needle. The following abbreviations are used in this manuscript: IoT Internet of Things; AI Artificial Intelligence; LED Light Emitting Diode; PCB Printed Circuit Board; DL Deep Learning; ML Machine Learning; NN Neural Network; OCR Optical Character Recognition. An end-to-end solution is proposed to detect and read the value of clear-face water pressure gauges placed throughout a PVC manifold network. Connected gauges communicate their data through an Arduino board and a node running a simple server. As the image acquisition device, the authors present the design of a given set-up consisting of a light strip positioning behind the gauge and a Black object to better contrast the gauge rod.

The computer vision module runs on a separate computer and consists of a Python script that uses open CV and TensorFlow libraries. Down-sampled images from the server are sent to the client and located in debt, read value by a decimal point detector followed by Optical Character Recognition (OCR) off. The following detection architectures are proposed: Faster RCNN; SSD; Retina Net. But when comparing separately the strategies and in conjunction with LeNet, the best results are achieved with a Rectangular Approach, even though they are distant from Faster RCNN and SSD results. The overall impression is that a somewhat constant optimal DSB ratio can somewhat compensate for a more prone model. Assumingly, a generalizable model can be trained using such a constant, making AG-DM falls in the ready-to-deploy category. Furthermore, it was demonstrated that the use of relatively small DSB values makes the trained model more tolerant to noise and provides better generalization to unseen data. At the leaf edge, it is argued that because the LED strip is positioned behind the gauge, smaller DSB values can be used, preserving enough lighting on the gauge transparent window to provide checker tessellation. In a gauge where a white area corresponds to a blank space and leads to a failure of this technique, the applied DSB is set to 1.0. The CIELAB conversion by pixel rather than by the whole image is addressed for the first time regarding measurements.

Equ 2: Predictive Maintenance Model (AI-driven)

$$M(t) = f(\Delta P(t), \Delta T(t), \Delta V(t), D(t))$$

Let:

- $M(t)$ = Maintenance probability at time t
- $D(t)$ = Diagnostic data over time t
- $F(t)$ = Failure risk prediction at time t

4. AGENTIC AI INNOVATIONS

A strategy is devised to distribute devices worldwide that can monitor smart city functions. The strategy deals with both stationary and portable devices and is formulated as a sensor distribution optimization problem. By considering an equidistant, city-wise, and street-wise distribution of cameras, the performance of a novel application may be improved. One of the strongest contenders in simulating and assessing complex phenomena is simulations. The computational load of this type of simulation may be high, especially for 3D systems, when fast cost-efficient evaluations are necessary for design purposes. A surrogate model is developed to create reduced-order models of high-fidelity simulations. This technique can create a balance between the accuracy of the results and the need to oversimplify the real-world problem.

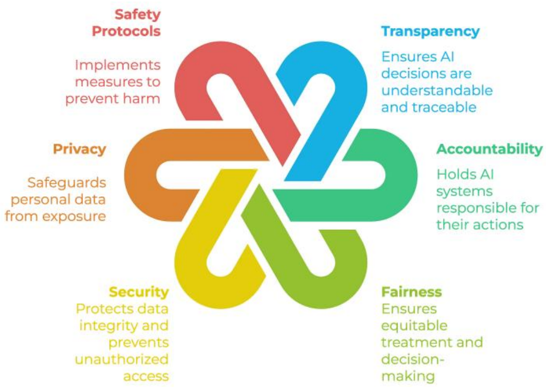

Fig 4: Agentic AI

4.1. Definition and Characteristics The machines are linked to a coordinating edge that can process the consumed information and communicate more complex issues with the cloud. This system of analytics servers that can sort through all incoming data and distribute structured information. Patterning algorithms will identify and notify rules to the next data-sorting server.

Industrial IoT makes many promises to streamline the manufacture of complex devices while maintaining quality and encouraging automation. The auto industry is embracing this technology as it strives to streamline engine production. This discipline stretches from the machines used on the assembly line to the devices that monitor the resulting engines. Making complex systems simpler results in models that reduce the deviation of parameters away from a normally predictable shape, simplifying the retooling needed between parts. The automotive industry generates petabytes of data every year, from which accurate predictions of system states must be made. A proposed mechanism is demonstrated in which vibration data acquired during engine testing can be used to predict electric motor lifetimes.

4.2. Applications in Manufacturing The works in product design and engineering informatics that establish capabilities for semi autonomous systems to innovate will become indispensable. In the end, the maker will be lauded as master. Better yet, circumstances will so control the actions of makers that they will find it nearly impossible to do other than innovate. This prospective scenario is inspired by the development of the Agentic AI Innovations paradigm. Based on the proprietary amiNXT technology platform synthesised in a DL model compressed to require only 350 discrete parameters, agentic AI innovations affords small and medium-sized manufacturers a gentle acceleration into the Industry 4.0 revolution. Here, a novel benchmarking methodology is introduced which will enable the unbiased and meaningful evaluation of agentic AI innovations by professional manufacturers. Four benchmarking pillars include manufacturing resilience, artificial raw maturation, next-generation workforce learning, and supplier social elicitation. Across these four pillars of development, 77 unique performance measures are defined. As an AI's operation and maintenance procedures are not fully standardised, the information will be presented in the form of text and image description regarding a step-by-step operation routine.

5. INTEGRATION OF IOT, HEARTBEAT MONITORING, AND AGENTIC AI

In response to a client's business partnership's request, it has been kindly proposed an end-to-end technological and business solution for a novel breathing Analog Gauge monitoring on a yoga household consumer brand. IoT within the solution enables an always-on vintage-inspired ambient Lighting-LED heartbeat counter beneath the gauge to display the monitored info, while an agentic AI would innovatively adjust the gauge (turning the lights on/off) at the monitored detected milestones. The heartbeat events are transparently detected by IoT and agentic AI from the breathing byte-array signal; the solution always supports various Analog Gauge types and brands. Design engineering details are provided for analog gauge harvesting and monitoring IoT PCB modules, a convetual TFT indicator PCB module, and the corresponding PCBV Prototypes, including the Gerber and BOM files. Bilateral non-disclosure JPEG files are attached so that the relevant B2B partners' agreements can be first signed to access the details. It is affirmed this yoga related use-case was never published end-to-end anywhere. The solution enables an Ambient LED to image processing heartbeat monitoring implementation on a consumer Electronic LED Gauge product brand; the detected heartbeat events then in a unique enhanced customer IoT experience are equally Agentic AI .

Equ 3: Real-Time Feedback Loop for Performance Tuning

$$\dot{x}(t) = A(t) \cdot x(t) + B(t) \cdot u(t)$$

$$y(t) = C(t) \cdot x(t)$$

Let:

- $x(t)$ = Performance variable (e.g., engine power, fuel consumption)
- $y(t)$ = IoT feedback signal (e.g., sensor readings)
- $u(t)$ = AI control signal

5.1. Synergies and Benefits The current landscape in academia and industry has been witnessing the rise of a plethora of studies regarding the Internet of Things (IoT) in many segments, all combined or not with Artificial Intelligence, Industry 4.0, Smart Manufacturing, or Smart City perspectives, among others. Old industrial practices and assets have been leveraged by new technologies and after-market solutions, canvasing a wide production of diverse sensors, actuators, smart devices, domotics, fleet management tools, and extensive automation capabilities, installed in smart homes, smart healthcare equipment and connected cars, but most visibly and significantly in production lines and industrial plants. The massive mountains of data generated by this all-encompassing IoT ecosystem, added to the collective increase in computing and storage capacities has driven the adoption of not only Big Data and cloud computing but also further Artificial Intelligence (AI) resources, such as data mining, machine and deep learning tools. Powered by these three primary pillars, the ensuing AIoT solution has forked novel grounds in prescriptive analytics, predictive and prescriptive maintenance, anomaly detection, computer vision, smarter and safer mobility, field management, swarm robotics, digital twin and countless other exciting fields shaping the future of the human society. Synergies and potential benefits stand out when IoT and AI technologies and assets are taken together. As it will be demonstrated, this is either captured in real-life applications or used for the sake of future exploitation and systems. For demonstration purposes, automotive, aerospace, electronic consumer goods, food and beverage, foundry, footwear, equipment and pets efficiency environments will be covered, each separately framed in recent or ongoing studies with real industries, municipalities, and academic partners.

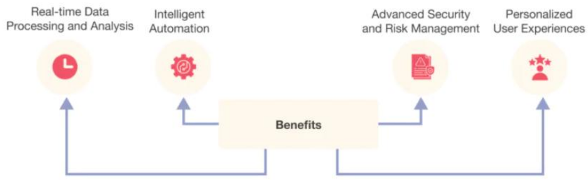

Fig 5: Benefits of Revolutionizing Engine Manufacturing

6. CASE STUDIES AND EXAMPLES

Recently, Design for X (DfX) methods and tools has become widely adopted by companies operating in innovative and competitive markets, among them the automobile and computer sectors. Most efforts have been devoted to the introduction of quality, manufacturing, reliability, materials, environment aspects into product development processes, focusing on the Company's supply chain. However, with the proliferation of sensors and wireless devices and the diffusion of the Internet of Things (IoT) paradigm, the opportunity to employ everyday objects as links in a data loop that efficiently manages services like healthcare and wellness has expanded. This perspective raises large opportunities, challenging existing businesses to work better and enhancing new emerging ideas to provide chargeable services. In a world dominated by a constant increase in demands and design complexity, the need for development strategies that go beyond DfX aspects is mandatory. Complexity management has been addressed by products approach, process simplification and optimizer design. Sometimes, this can result in missed environmental conditions that occur during the life cycle of products. Moving towards a product-service system approach, manufacturers can extend the customer-supplier relation onwards to the point of sale, to include the operation, maintenance and end-of-life stages. However, to be effective, enhancement requires a very stringent multi-disciplinary and cross-chain integration process, not easy to achieve for multi-tier companies that must deal day-by-day with competition, constraints and standardization. The aim of manufacturing needs is to provide a comprehensive analysis of an innovative roadmap that can be tailored for big companies, but is also flexible enough to be used by small and medium enterprises. Starting from the state of the art and industrial cases, it stimulates the manufacturing companies to open a debate toward the design of a product-service system innovative model that goes beyond the current one. A typical flow chart of the possible step-by-step approach is proposed; the approach is currently under implementation in the automotive and computer business sectors, although it can be extended to other chains.

Fig : An IoT-Based Smart Framework for a Human Heartbeat Rate Monitoring and Control System

6.1. Real-World Implementations Industrial music could be considered unique in that it has an uncommon degree of prominence in its name — it is music, often made from machines, about other machines. Its era of peak prominence was the late 1970s and 1980s when data was making its way from cabinets of punched cards to miners of virtual bitcoin. As eruptions of steam power and division of labor have been used as working periodizations, it could be said industrial music is fast becoming a "postindustrial concern." In a twist of fate, it is often easier to answer, "What isn't industrial music?" Sites of assembly, assemblage, fissure, explosion, workers, robots, cyborgs, feedstock, waste, and every permutation in-between, it could be said industrial music parades the discursive fullness of its parentage in manufacturing.

Digitally-controlled manufacturing, or digitalization of the manufacturing shop-floor, can be seen as representing an epochal moment in both economic and artistic practice. As with the spate of Y2K-inspired subgenre names and the subsequent stymying of genre parsimony, the so-called fourth industrial revolution has entered into a mode of terminological inflation: IoT platforms, big data, machine learning, cloud manufacturing, cyber-physical systems, fog computing, advanced robotics, system of systems — the effect is Turing-complete naming sired from agnostic seamlessness. On an empirically tame basis it could be said the digital revolution in manufacturing only follows from the spread of digital.

7. CONCLUSION

The focus of this text is to revolutionize engine manufacturing by integrating AI and IoT technologies via developing an IoT-driven heartbeat monitoring system with striking innovations of the marketing leading agentic AI solutions. By leveraging recent advances in engineering, this IoT setup is implemented with a mid-tier analog engine monitor to capture engine data signals and output values. Specifically, engine cylinder head temperature and exhaust gas temperature are monitored continuously.

Banking on the prosperity of IOT, agentic AI, and hardware-software integration, this agentic IoT system demonstrates not only instant engine health status updates for technicians matching the leading aviation solutions, but also (at least) accurate marketing opportunities using the AI-driven approach. In both, a heartbeat monitor-shaped API key is connected to the IoT platform. Pulsars generate message requests and send them to the respective IoT device. IoT readings are fed back to the pulsar as insights, which in return posts the related action to the IoT platform, i.e., API health status update for the technician and hit/lead on the ad. In the agentic AI system (post dynamics), agentic elements, capable of deciding to feed necessary information initially learned, generate a sequence of learning requests at intervals (Ask feeds). Vision optics translations of instrument readings are taught to the main AI element, the Vision AI solvers, leading to flexible accommodations of any engine monitor model. The solvers continuously post the corresponding output readings to the monitor status. If a deviated consequence is derived, a self-action mechanism triggers another pulse instructing the vision solvers to correct the original readings. Bench setups reveal that the AI equipped system successfully imitates a human technician and resolves monitoring challenges for a wide variety of engine monitor products achievable only with free-hand vision assistance.

7.1. Summary of Key Findings Manufacturing is the core activity of the G20 industry, and making the best use of advanced manufacturing technologies, such as IoT enabled AI-driven Robotics, is a critical factor for staying competitive. AI-driven robotics is expected to comprehensively gather, analyze, and standardize data automatically acquired using cogeneration with virtual and actual dynamization models. This approach significantly shortens the downtime for setting change, which is a nuisance for small lot productions and a critical factor in maintaining competitiveness in the international market. The resulting benefits expand also to increase the quality of designing products, thanks to the reduction of the intervention of human factors that generate noises, and to increase the know-how productive, thanks to the reuse of models developed and preserved over time.

Reliable and secure manufacturing is another major topic. The IoT and network society create a risk environment that increases vulnerability to attacks such as information theft and impacts on the controller, which may be sabotage. In response to these requirements, it develops a system that can tolerate and restore as much as possible from the occurrence of these accidents in a limited state of sharing only manufacturing results. The heartbeats, which are the signals that continually reflect the operating state of the machine, are monitored by smart IoT.

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