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Implementation Of Machine Learning Algorithms In Industry In The Modern Age

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Abstract: In the Modern age of industrialization, increasing competition, increase in competitors global-ly and rapid increase in demand to meet the local and global requirement with correct quality and standards to satisfy the needs of the customer and matching new rising needs which re-quire change in design, product standards machine learning is a strong need for implementation in the industry.

Index Terms **-** Industrialization, Modern Age, Machine Learning, industry 4.0, Predictive Maintenance, Computer Vision, human Resource Management, Decision Making, Telecommunication, Education Industry**.**

I. Introduction

It is a known fact that without the use of technology, innovation and industrial breakthroughs industrialization would not have been impossible which means that the direct causes had to be sought in the past of the science and the technology. [1]

The new economy has seen tremendous strides since its early appearance at the onset of the industrial revolution in the 18th century for decades much of the items including guns tools food clothes and homes have been crafted or used from work by animals this improved in the late 18th century with the introduction of the industrial methods industry development was then a quick uphill climb leading up to the next manufacturing age fourth era the summary of this evolution will be discussed here this article takes a theoretical approach to looking at business as the fourth generation this study identified three key elements of each transformation to understand insight of the phenomenon technological economic and demographic changes in business public use of technology put extreme competition and ageing demographics will allow the expansion quicker and broader although advances in business with machine learning implementation are more evaluative than transformative their mixture and the context in which they develop forecast significant economic and social impacts that will in turn constitute a revolution [2].

Table1: Literature Regarding 4th Revolution [12]

Ref No.	Author with Year	Critical Findings
3	A. Maier (2015)	Type of improvement techniques applied
4	Lee. Et al 2015	Decision Algorithms
5	Spath, Ganschar, Gerlach, Hämmerle, Krause & Schlund, 2013	Simulation Technology
6	Wan, Cai & Zhou, 2015	Focus in customer demand

7	Weiss, Zilch & Schmeiler, 2014	implementation strategies & Benefit of industrial Revolution
8	Shah and Ward (2007	Discussed the technologies and concepts of Industry 4.0
9	Dora-ven Gourberrgen & Gellynck 2013	Factor effecting in 4th Revolution
10	Field & Hoff mann 2014& Posada et al. 2015	Introduction of robotics and automation Technology.

The following timeline shows how industrialization has grown from its prehistoric period till date.

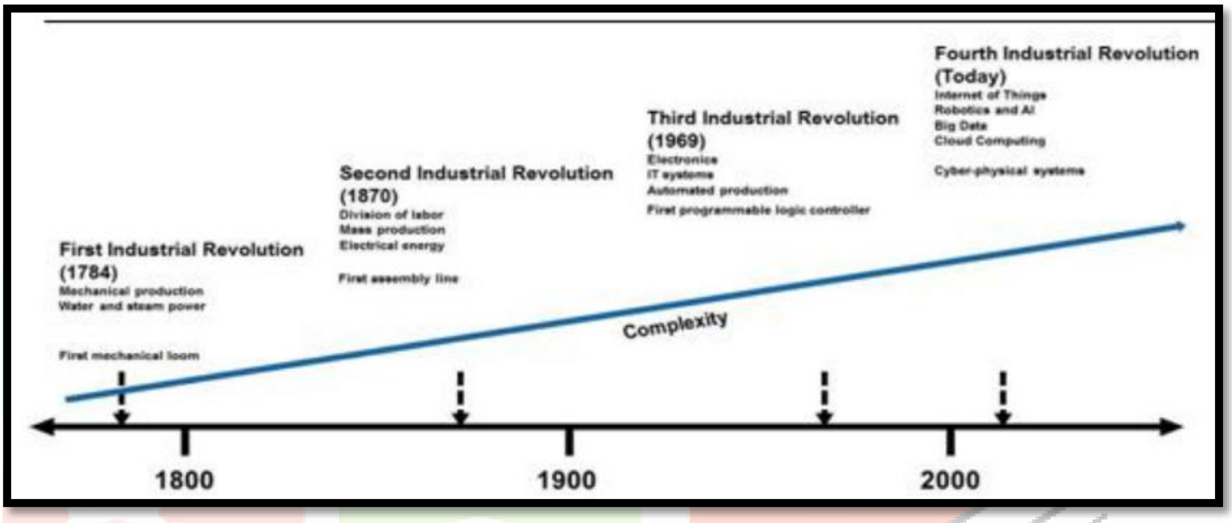

Fig 1. Time Line Chart Industrial Revolution Period [11]

Table: 2 New Technology in Todays Industry [12]

Technology Trend	Technology Used	Application of Technology
Latest Technology	- Internet of Things (IoT) - Cloud Computing - Big Data - Robotics and Artificial - Intelligence (AI)	- Sustainable Agricultural - Manufacturing - Bionics - Renewable Resources - Human Robot Coordination

II. Implementing Machine Learning in Industry

Today many companies see Artificial Intelligence (AI) and there in particular field of Ma-chine Learning (ML)as an important strategic component with which they want to achieve competitive advantage. There is a large potential of Machine Learning Techniques in manufacturing applications. These methods are specifically used for predictive maintenance which helps in minimizing unforeseen failures and improvement in the availability of machine and equipment, also, a large opportunity for the process optimization.

For the development of the method for the standardized introduction and value-added use of ML projects, a literature research was carried out, as well as different solutions of numerous consulting providers in the market were examined. [13] and [14] provide a broad overview of data mining process models. Considering the relevance, SME focus and applicability the following models have been selected and will be presented briefly.

CRISP-DM (Cross-Industry Standard Process for Data Mining), a general process model that has been developed and tested for a long time, is used to examine historical data stocks. CRISP-DM splits the data mining process into six main phases: business understanding, data understanding, data preparation, modelling, evaluation, deployment [15].

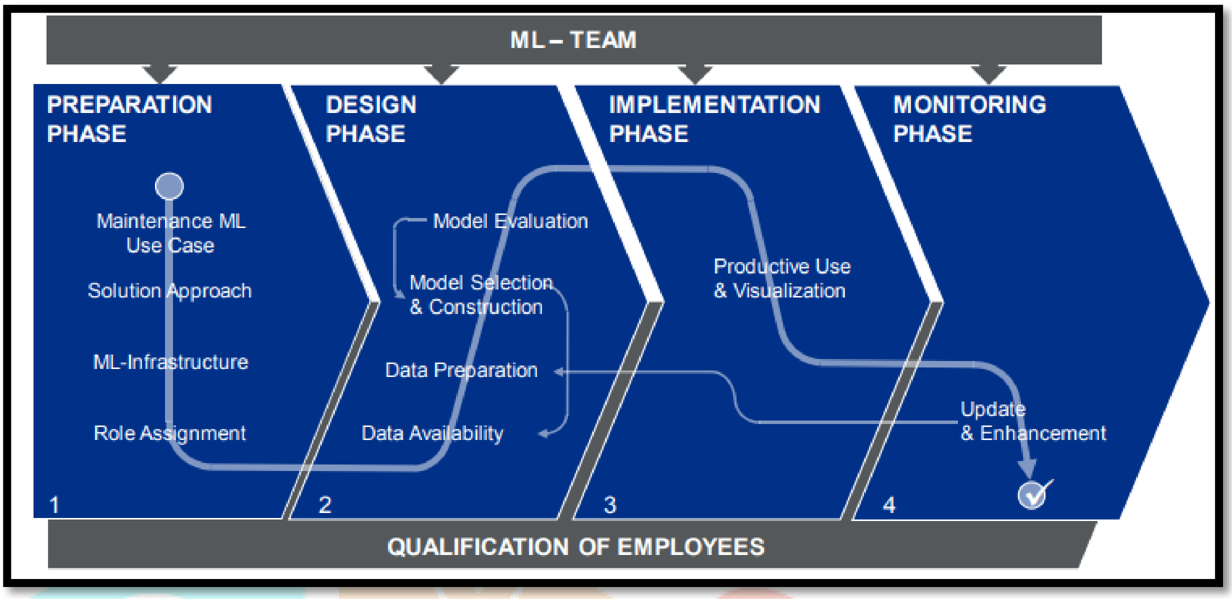

Fig.2 Method for Implementation of Machine Learning Solutions

III. Fields of Application

Many industries have started to adopt intelligent algorithms to automate and enhance prediction making processes for a wide range of business applications. In the manufacturing industry – for example – such intelligent algorithms may provide additional value in a businesses' maintenance and quality control strategy. This paper will provide a series of technical implementations regarding the implementation of machine learning software for predictive maintenance and quality control support within the manufacturing industry.

3.1Predictive Maintenance

To reduce mechanical component failure, most manufacturing companies rely on the concept of preventive maintenance [1]: maintenance programs – including routine work, component change, reparation of detected components, and regular inspections – after a pre-defined duration of operations. However, classic maintenance schedules like preventive maintenance have some inherent shortcomings:

Over-Maintenance: More than often, the inspected component is still in perfect condition, resulting in unnecessary maintenance procedures and component handling.

Reduced Manufacturing Capacity and Revenue Loss: Preventive maintenance requires manufacturing machines to be taken out of service, irrevocably resulting in reduced manufacturing capacity and revenue losses.

Incidental Damages: Regular maintenance requires invasive actions - such as disconnecting electric cables, loosening and tightening bolts, and removing mechanical components - which may cause incidental damaging of secondary components.

In predictive maintenance, advanced statistics and predictive models are used to estimate the condition – and possibly predict the future failure – of mechanical components. This poses advantages when compared to classic preventive maintenance schemes:

• Cost Reduction: Mechanical components are only repaired or replaced when indicated by the algorithm. This reduces both the labour cost (maintenance staff) and the cost re-quired for spare parts (inventory cost and actual component cost).

• Reduction in Secondary Damages: By identifying potential component failures, manufacturing companies can reduce the financial losses incurred by secondary damages when component failure occurs. This because failed components have the tendency to damage other - usually nearby – components, resulting in an aggregated cost in the case of component failure.

• Reduced Outage Time: Predictive maintenance results in a reduced number of maintenance interventions, thereby reducing the outage time and increasing the manufacturing capacity. The expected annual benefits β ($ per year), can be estimated by:

$$\beta = P(s) \cdot (\beta f + \beta s) \qquad (1)$$

With β the total annual benefits, P(s) the probability of successful of early component failure detection, βf the benefit due to the decrease in outage time, and βs the benefit due to forced outage time becoming scheduled outage time.

a step-by-step framework which allows the creation of a data-driven model to aid manufacturing companies in implementing a predictive maintenance strategy for mechanical systems [16][17]:

Step 1: Data collection Collect data from the degradation process of the component of interest. This data includes component wear after certain usage time, average component failure time, and ambient component characteristics during operation.

Step 2: Determine degradation type Component degradation may follow a linear, exponential, power, or logarithmic degradation process with respect to component usage. This degradation type needs to be determined and may depend on ambient conditions and material properties.

Step 3: Machine Learning regression model Build a regression model (using machine learning methodologies), by taking into consideration the obtained data and specified component degradation characteristics.

Step 4: Use obtained models for inference. The obtained model (one model per component or system) can be used for inference about the degradation process of similar components – i.e., identical components operating in similar ambient characteristics – and detect future component failure and wear.

Step 5: Use Inference results for Predictive Maintenance Decision Making Inferred stages of component degradation (obtained in step 4) are used as an input to the predictive maintenance program of manufacturing companies. Taking into consideration required safety regulations, industry-specific safety factors, and machine availability, optimized maintenance schedules for specific components (as well as entire systems) can be determined.

Step 6: Iterate, Update Data, and Improve Inference As time passes, more degradation data and component failure data become available. By establishing a constant data-pipeline from the data collection (step 1) to the degradation type determination (step 2) and machine learning model training (step 3), the results from the model inference (step 4) can be improved, allowing manufacturing companies to optimize their predictive maintenance strategy (step 5) in a continuous way.

3.2 Component Defect Detection using Computer Vision

Most component defects are caused by irregularities in manufacturing systems such as overheating, excessive machine loads, machine component wear, and faulty calibrations. Component defects resulting from such abnormal operating conditions can – usually – be detected by machine learning classifiers which have been trained on aggregated quantitative data obtained during the production process

In general, convolutional neural networks require several layers of filters, with the most common layers – usually referred to as 'the building blocks' – being the convolutional layer, the maxpooling layer and the fully connected layer [18]

• Convolutional Layers Convolutional layers consist of a set of cube-shaped filters which are convolved with either the input image, or the output data from the previous layer. These convolutional filters are slid over the input data and are used to compute the dot product between the pixel values within the area of interest and the filter weights – resulting in what is commonly referred to a 'convolved feature maps [19].

• Pooling Layers Pooling layers are periodically inserted in between the different layers of convolutional networks and are responsible for reducing the size of the convolved features obtained in previous layers. Their main purpose is to reduce the computational pow-er that is required for processing the imagery input data [19].

• Fully Connected Layers Fully connected layers are added at the back of the convolutional neural network and take as an input the flattened vector-representation of the previous layers – being the convolutional layers and max-pooling layers. In essence, the fully-connected layers represent a regular neural network classifier which – instead of being trained on quantitative data as is the case with regular neural networks – is trained on the detected features within the component images [19].

• Network Output The output from the fully connected layer is a one-dimensional vector which contains the probabilities of the input image belonging to a certain class. Usually, the network's predicted value - i.e., the network's output - is determined by taking the class – i.e. the type of component defect - that is associated with the highest probability within this one-dimensional probability vector [19].

3.3 Machine Learning in human Resource Management

This study uses machine learning (ML) techniques to manage and analyze human resource data in modern enterprises. The ML techniques realize the functions of the human re-source system and reduce the business volume in human resource in order to improve the efficiency and management of the human resource work. In this paper, we designed and implemented the wage forecasting model in human resources that uses a gradient descent algorithm, its types, and backpropagation (BP) neural network to improve the accuracy of the forecasting model. We performed multiple experiments by using a various number of neurons in the hidden layers, different number of iterations, and several types of gradient descent algorithms. The BP neural network model was performed brilliantly by attaining the training accuracy of 89.98% and validation accuracy of 84.05%. The experimental results show the significance and importance of the proposed work [20].

3.4 Machine Learning in Decision Making

Decision strategies in dynamic environments do not always succeed in producing desired outcomes, particularly in complex, ill-structured domains. Information systems often capture large amounts of data about such environments. We propose a domain-independent, iterative approach that (a) applies data mining classification techniques to the collected data in order to discover the conditions under which dynamic decision-making strategies produce undesired or suboptimal outcomes and (b) uses this information to improve the decision strategy under these conditions. In this paper, we formally develop this approach and illustrate it by providing detailed examples of its application to a chronic disease care problem in a healthcare management organization, specifically the treatment of patients with type 2 diabetes mellitus. In particular, the proposed iterative approach is used to improve treatment strategies by predicting and eliminating treatment failures, i.e., insufficient or excessive treatment actions, based on information that is available in electronic medical record systems. We also apply the proposed approach to a manufacturing task, resulting in substantial decision strategy improvements, which further demonstrates the generality and flexibility of the proposed approach [21].

3.5 Machine Learning in Telecommunication Industry

With the development of the 5G and Internet of things (IoT) applications, which lead to an enormous amount of data, the need for efficient data-driven algorithms has become crucial. Security concerns are therefore expected to be raise during state-of-the-art information technology (IT) as data maybe vulnerable to remote attacks. As a result, this paper provides a high-level overview of machine-learning use-cases for data-driven, maintaining security, or easing telecommunications operating processes. It emphasizes the importance of analyzing the role of machine learning in the telecommunications sector in terms of network operation. [22**].**

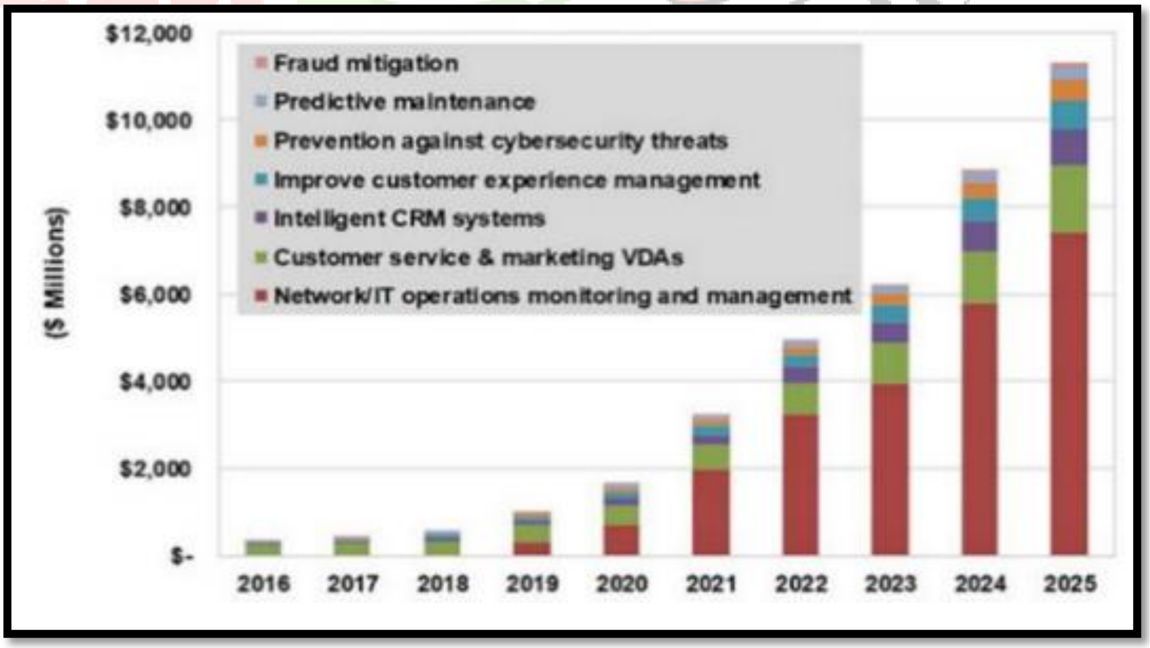

Fig.3 Investments in ML by use-case [23]

3.6 Machine Learning in Education Sector

Application of machine learning in education: Artificial intelligence and Machine Learning can significantly impact the future of our education. With machine learning, we are moving away from the one-size-fits-all methodology. It is an effective teaching tool be-cause of its ability to adapt and offer customized curricula. Machine Learning enabled tools help assess an individual's current level of understanding, identify gaps in the learnings of the student and provide real-time solutions. The technology can also identify areas where teachers are outnumbered by students and create optimized learning programs that impact the largest number of students. Here are some advantages of ML that shows it be-come a game changer in the field of education [24].

•Predict Student Performance [24]
•Grade Students Fairly [24]
•Organize Content Effectively [24]
•Suggested learning path [24]
•Career Path Prediction [24]
•Group Students and Teachers [24]

IV. Conclusion

In the view of the above study and related literature review supports the fact that the Modern Age is moving toward an era where the Machine Learning is kept at the central core of the business and its operation in almost all the sectors. The advantage is that it makes the processes involved in the planning, management, implementation, decision making, quality control, process control and other factors become more efficient, reduction on cost and error free.

References

[1] https://www.researchgate.net/publication/282572543 The Industrial Revolution Chapter · January 2008, Author: Peer Vries READS 58,362 1 author: Peer Vries 105 PUBLICATIONS 413 CITATIONS.

[2] International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-11, September 2020, Evolution of Industrial Revolutions: A Review Ashwani Sharma, Bikram Jit Singh, Retrieval Number: 100.1/ijitee.I7144079920 DOI: 10.35940/ijitee.I7144.0991120, Published By: Blue Eyes Intelligence Engineering and Sciences Publication.

[3] Thomas A., Lewis G.: Developing an SME-based integrated TPM-Six Sigma strategy, International Journal of Six Sigma and Competitive Advantage, Vol. 3, pp 228–247, 2007.

[4] Zhang, Z.; Liu, S.; Tang, M.(2014) Industry 4.0: Challenges and Opportunities for Chinese Manufacturing Industry. Technical Gazette 21, 6, III-IV

[5] Porter, M. E. (1994). The role of location in competition. Journal of the Economics of Business, 1(1), 35-40

[6] Venohr, B., & Meyer, K.E. (2007). The German miracle keeps running: How Germany's hidden champions stay ahead in the global economy. Working paper. Institute of Management, Berlin School of Economics, Berlin, Available at SSRN 991964, March. http://dx.doi.org/10.2139/ssrn.991964

[7] Freeman, C., & Soete, L. (1997). The economics of industrial innovation. Psychology Press

[8] Dora, M., Van Goubergen, D., Kumar, M., Molnar, A., & Gellynck, X. (2013). Application of lean practices in small and medium-sized food enterprises. British Food Journal, 116(1), 125-141. http://dx.doi.org/10.1108/BFJ-05-2012-0107

[9] Brettel, M., Friederichsen, N., Keller, M., & Rosenberg, M. (2014). How virtualization, decentralization and network building change the manufacturing landscape: An Industry 4.0 Perspective. International Journal of Mechanical, Industrial Science and Engineering, 8(1), 37- 44

[10] Hoerl R.W.: Six sigma black belts: What do they need to know?, Journal of Quality Technology, Vol. 33, No.4, p. 391- 406, 2001

[11] Lee, J.; Kao, H.A.; Yang, S. Service innovation and smart analytics for industry 4.0 and big data environment. Procedia CIRP 2014, 16, 3–8. [CrossRef]

[12] Ashwani Sharma, Bikram Jit Singh, International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-11, September 2020, 66-73.

[13] Kurgan LA, Musilek P. A survey of Knowledge Discovery and Data Mining process models. The Knowledge Engineering Review; 2006;21(1):1–24.

[14] Kozjek D, Vrabič R, Rihtaršič B, Lavrač N, Butala P. Advancing manufacturing systems with big-data analytics: A conceptual framework. International Journal of Computer Integrated Manufacturing; 2020;33(2):169–88

[15] Rebecca Welte, Manfred Astler, Dominick Lucke, A Method for Implementation of Machine Learning Solutions for Predictive Maintenance in Small and Medium Sized Enterprises, Procedia CIRP 93 (2020) 909–914, Available online at www.sciencedirect.com

[16] Lin, J., Pulido, J., & Asplund, M. (2015). Reliability analysis for preventive maintenance based on classical and Bayesian semiparametric degradation approaches using locomotive wheel-sets as a case study. Reliability Engineering & System Safety, 134, 143-156.

[17] Korvesis, P. (2017). Machine Learning for Predictive Maintenance in Aviation (Doctoral dissertation)

[18] Namatēvs, Ivars. (2017). Deep Convolutional Neural Networks: Structure, Feature Extraction and Training. Information Technology and Management Science. 20. 10.1515/itms-2017-0007**.**

[19] Wu, J. (2017). Introduction to convolutional neural networks. National Key Lab for Novel Software Technology. Nanjing University. China, 5, 23.

[20] Hong Zhu, Research on Human Resource Recommendation Algorithm Based on Machine Learning, Special Issue Scientific Programming for Smart Internet of Things, Research Article | Open Access Volume 2021 | ArticleID 8387277 | https://doi.org/10.1155/2021/8387277, Hong Zhu, "Research on Human Resource Recommendation Algorithm Based on Machine Learning", Scientific Programming, vol. 2021, Article ID 8387277, 10 pages, 2021. https://doi.org/10.1155/2021/8387277

[21] Meyer, Gediminas, & Johnson, 2014, A Machine Learning Approach to Improving Dynamic Decision Making, June 2014 Information Systems Research 25(2):239-263, DOI:10.1287/isre.2014.0513

[22] Haitham Hassan H. Mahmoud & Tawfik Ismail2, A Review of Machine learning Use-Cases in Telecommunication Industry in the 5G Era, Conference Paper · December 2020 DOI: 10.1109/ICENCO49778.2020.9357376

[23] Anon, (n.d.). Telecommunications Industry Investment in Artificial Intelligence Software, Hardware, and Services Will Reach $36.7 Billion Annually by 2025 | Omdia | Tractica. [online] Available at: https://tractica.omdia.com/newsroom/pressreleases/telecommunications-industry-investment-in-artificialintelligence-software-hardware-and-services-will-reach-36-7-billionannually-by-2025/ [Accessed 10 Jul. 2020].

[24] Anjali Jagwani, A REVIEW OF MACHINE LEARNING IN EDUCATION, 2019 JETIR May 2019, Volume 6, Issue 5, www.jetir.org (ISSN-2349-5162), Pg 384-386