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An Integrated Machine Learning Model for Manufacturing Industry

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Abstract

The purpose of this article is to examine the process of developing services based on machine learning technologies in a manufacturing environment context. Over the past decade, there has been a resurgence of interest in technology, with prominent technology business organisations and several start-ups incorporating it into their operations. The technology's widespread applications capacity for obtaining a competitive advantage, combined with the prospect of task automation for increased operational efficiency, renders it a significant resource for large corporations. Yet, the rate at which most of manufacturing firms are implementing Machine Learning services into their operations is very insignificant. Technical expertise has dominated study in this field, with minimal participation from other areas. Thus, the goal of this article is to identify the development benefits of Machine Learning services and to provide a process model for their deployment, based on service development and value theory.

A. Introduction

Today's modern manufacturing sector is going through a never-before-seen rise in data availability. These information come in a range of forms, interpretations, and quality levels, for example, sensors data from the production line, ecological data, and machine tool variables. This phenomena is referred to by a variety of terms, including Industrial Revolution 4.0 (Germany), Smart Manufacturing (United States of America), and Intelligent Factory (South Korea) [4-29]. Big Data is frequently used to refer to the growth and availability of enormous volumes of data. The accessibility of, for example, quality-related data enables the possibility of sustainably improving the quality of process and product. Nevertheless, it has been acknowledged that an abundance of information might offer a problem and might have a detrimental effect, as it can divert attention away from the primary concerns or result in delaying or incorrect judgments regarding suitable measures [7]. Generally speaking, the manufacturing sector should recognize that in order to take full advantage of steadily increasing data availability, such as for quality improvement programs, manufacturing estimated cost and/or performance improvement, and an improved knowledge of consumer's needs, etc., assistance is required to manage the high dimensional data, variability, and complexities involved. Latest advancements in some fields such as mathematics and computer science and the provision of simple-to-use, frequently free (software) instruments have the potential to significantly reshape the manufacturing field and their understanding over the growing manufacturing datasets. Among the most intriguing areas of research is Machine Learning (ML) [1]. Nevertheless, the area of ML is extremely varied, with several accessible algorithms, concepts, and approaches. This constitutes a hurdle to many manufacturing practitioners' use of these powerful technologies, and hence may impede their exploitation of the massive volumes of data that are becoming more available. From this backdrop, the present paper aimed at developing an integrated Machine Learning Model to elucidate why machine learning is a relevant and promising solution for the current's and future industrial issues [4].

B. Machine Learning

Machine learning is defined as "the ability of computers to find solutions without being explicitly programmed to do otherwise". The implementation of machine learning techniques has grown exponentially in recent years as a result of the availability of huge volumes of data, advancements in digital technology, and the increased capability of accessible machine learning tools. Additionally, machine learning has been utilized in additive manufacturing for a variety of purposes, such as process optimisation, dimensional correctness measurement, manufacturing defect identification, and material property prediction. The purpose of this study is to offer an integrated ML to elucidate why machine learning is a relevant and promising solution for the current's and future industrial issues[16]. The approach is focused mostly on the integration of machine learning into the Operational Technology of manufacturing process in order to discover opportunities behind this concept. Due of the ease with which an ML-based output-input model can be created given input-output data, an integrated model based on machine learning may accomplish reversed design without the need to develop complicated connection equations[20].Thus, even if data were created as structure-property connections, property-structure relationships may be directly represented. Additionally, if sufficient data is provided, machine learning-based models have almost no constraints on the complexity of the design issue. Additionally, the major benefit of machine learning over other surrogate modeling techniques is its capacity to model input-output connections in both directions, allowing for reversed design. The suggested machine learning-based integrated design technique can acquire the objective design directly from the property requirements, which is not possible with the typical surrogate model-based design process. It Should be noted that numerous studies have examined the application of machine learning in a variety of manufacturing enterprises. This section discusses several examples of intelligent machining systems that use machine learning, as indicated in Table 1. Because the underlying concepts of the various types of machine learning techniques are well-known, just the details of the machining operations are given. The most often researched aspect of traditional machining is its relationship to the usage of machine-learning techniques. The objectives differ wildly, going from operating parameters optimization to machine healthcare applications and product quality improvement. The most often researched traditional machining techniques were milling and turning. The next section presents some applications of ML algorithms in manufacturing industry.

Table 1: Examples of machine learning-based machining operations

Authors	Process	Purpose	Algorithms	Input parameters
[33]	Milling	Tool wear measurement	artificial neural network; support vector machine	Tool image
[34]	Milling	Detection of tool failure	, support vector machine; support vector regression	Data on material removal rate and energy requirements
[35]	Milling	Projection of tool failure	random forest	Vibrating, material removal rate, and acoustic radiation
[36]	Milling	Estimation of electricity usage	Gaussian process regression	Velocity of the spinning, feed pace, cutting height, operative tool axis, and

				cutting technique
[37]	Milling	Forecast of tool failure rate and residual useful life	support vector regression	Motion, cutting depth, and acoustic emissions
[38]	Milling	Forecast of electricity usage	Gaussian process regression	Spinning frequency, rotational speed, and cut motion of the active tool
[39]	Milling	Diagnosis of tool failure	probabilistic neural network	Velocity of the spindles, flow rate, cutting width, maximum peak pressure, optimum variation packing pressure
[40]	Milling	Optimizing the course of the tool, the tool classification, the cut settings, and assessment of the recommended resolution.	Non- dominated sorting genetic algorithm II	Computer - aided design model
[41]	Milling	Projection of material properties	support vector machine	Machining velocity, cutting height, and flow rate
[42]	Milling	Estimation of chatter stabilization lobe	support vector machine	Vibration signal

[43]	Milling	Assessing the quality of tools	J48 Decision Tree	Vibration signals
[44]	Milling	Measurement of the cutting parameters	backpropagation neural network algorithm	The substance, the trimming substance, the coatings, the dimension of the tool, the cutting force, the feed rate, and the depth of cut
[45]	Milling	Estimation of deflections during machining procedures on thin-walled workpieces	Bayesian learning method	Historical data on dislocation

2.1 Artificial Neural Network (ANN)

Actually, ANN evolved from biology, whereby the Neural Networks (NN) contributes significantly to the mankind brain. ANN is a type of smart computing approach inspired by biological neurons. It is a highly parallel computational network consisting of an enormous set of fundamental processing units connected via a huge number of linkages. Rather of adhering to a body of regulations established by experts, ANNs understand the fundamental policies through a series of relevant metaphoric circumstances [29]. They are composed of at least three tiers (an input nodes, many hidden nodes, and an output nodes). Additionally, most of ANNs get their analytical activity from the relationships between their system unit operations. Owing to its ability to understand from experiences, ANN systems are usually used in a wide variety of disciplines of study[17]. Additionally, ANNs approaches outperform other standard machine learning techniques when dealing with binary code, fuzzy data, and non-linear data. ANNs are best suited for networks with a sophisticated, large-scale structure and unstructured data.

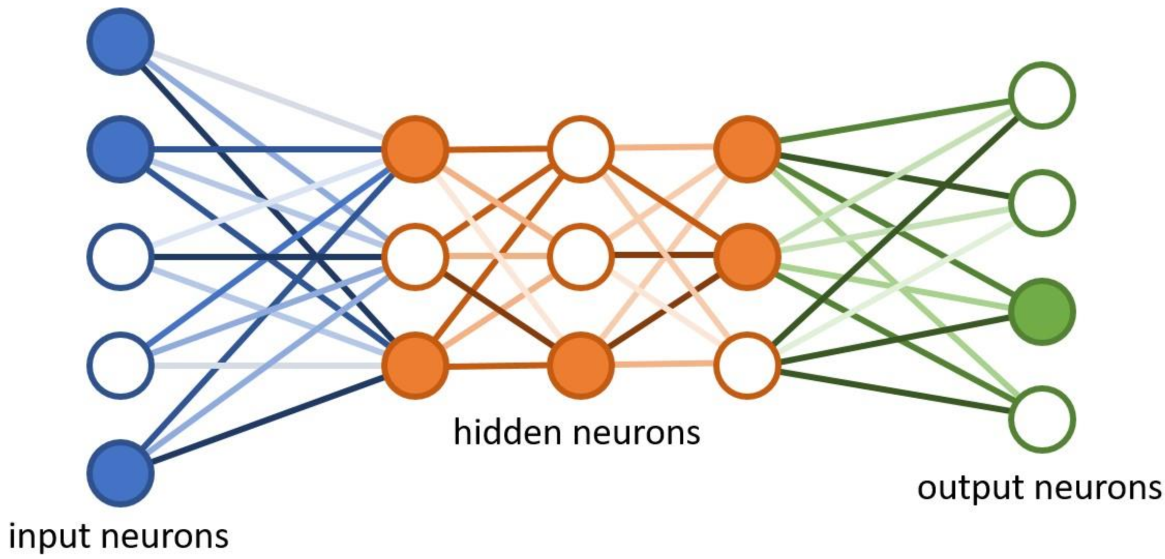

Figure 1: Basic structure of Artificial neural Network

ANNs are extensively used and are the most often used machine learning techniques, but they have also been proposed for various industrial applications including soft sensors and anticipatory control mechanisms [4]. [29] used velocity data to train an ANN model to categorize the tool state of a Computer Numerical Control (CNC) milling machine. The suggested research took a retrofit strategy in order to assist older systems in transitioning to Industrial revolution 4.0. A programmed prototype system coupled with designed sensing devices was used to monitor wear rate. The research confirms that adapting older equipment is possible. The developed model's performance was compared to that of Support Vector Machine (SVM). [29] suggested a method for treating and converting vibration data collected from a vibration system that simulated a motor and creating a set of data and testing an Artificial neural network model able of forecasting the future status of the system, including when a failure may occur. The approach comprises categorizing the database and creating a mechanism for determining the oscillating system's probability of failure using frequencies and amplitude data.

2.2 Bayesian Network

Bayesian network is a popular machine learning approach for fault detection. Bayesian network is a directed acyclic network in which the nodes represent random variables and the directed arcs connecting the nodes indicating their conditioned dependence [30]. To model an issue employing Bayesian network, the network topology should be specified, and also the probabilities associated with every node. Several researchers suggested the use of a variety of techniques to generate tree topologies that illustrate the cause and effect connection between these nodes [31].

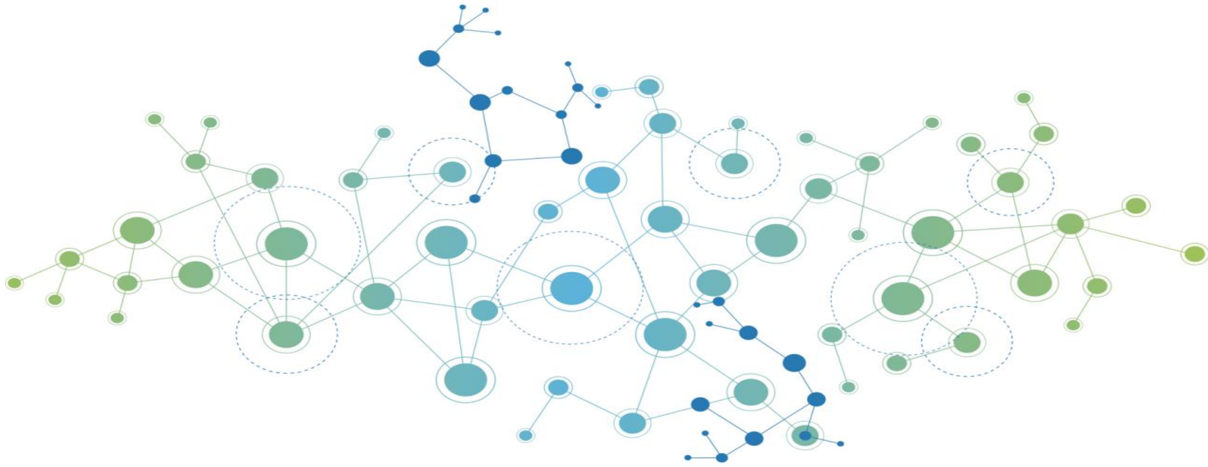

Figure 2: Structure of Bayesian network

[4] and [29] recommended the utilisation of failure mode and effect analysis (FMEA), [5] [6] proposed the use of fishbone diagrams (cause and effect diagrams), [5] proposed the use of fault-tree analysis and variation sensitivity matrix, and [7] proposed the use of finite element analysis Exact tree structure building for a Bayesian network using data is an NP-hard optimization issue [8]. [30] and [31] generated trees from data using the K2 [11] and [12] methods, respectively. [13] derive the cause-effect connection for the equipment being diagnosed from the maintenance handbook for the equipment. The network's conditional probabilities are then generated using process data collected from sensors and recorded in manufacturing execution systems (MES) or maintenance databases. Bayesian network is used in a variety of manufacturing industries. [9] and [6] utilized a Bayesian network to analyze the effect of process variables on wafer quality in order to determine the underlying cause of faulty wafers using historical process data. Additionally, the car industry [7] uses Bayesian network to identify fixture faults in taillight assemblies, and machining [10] uses BN to diagnose surface roughness faults. Quality management systems (QMS), manufacturing execution systems (MES), recipe management systems (RMS), computerized maintenance management systems (CMMS), and coordinate measuring machines are all possible data sources (CMM).

2.3. Support Vector Machine

SVM employs a variety of kernel functions, such as the radial basis function (RBF) or the polynomial kernel, to choose the optimal higher dimensional space for classifying data, and performs well with small training dataset [23-30]. SVM has been successfully applied in a variety of fields, including facial recognition software, handwritten character recognition, voice recognition, image retrieval, and forecasting [22-24]. SVM is often used within flaw detection, albeit not as frequently as BN and ANN [25].

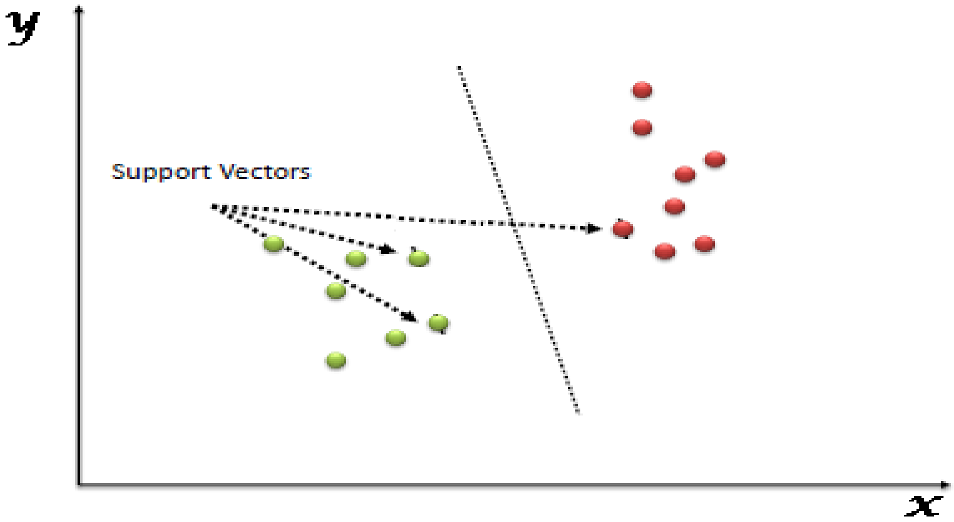

Figure 3: Structure of Support Vector Machine

[26-30] utilized the approach to identify gear failure during a face milling operation with changing cutting conditions. [27] developed a MapReduce programming model for automated diagnosis for cloud-based manufacturing employing SVM as the classification model and verified it with a study case of defect detection utilizing information from the UCI Machine Learning Repository on steel plate production [28]. [23] utilised SVM regarding classification of nine failure condition within a modular production system (MPS) utilizing data from eight sensing devices. He experimented with four distinct kernel functions, namely RBF, sigmoid, polynomial, and linear, and obtained a classification rate of 100 percent for all but the sigmoid kernel that had a classification rate of 52.08 percent. The same dataset was also subjected to decision tree techniques created employing the QUEST (Quick, Unbiased, and Efficient Statistical Tree), C&RT (Classification and Regression Tree), and Classification algorithms of 100 percent and a Chi-square automatic interaction detection (CHAID) rate of 95.83 percent obtained [23]. SVM and decision tree algorithms, Demetgul found [23], are extremely excellent monitoring and test equipment for important manufacturing systems. The SVM approach is effective for modeling both linear and non-linear relations. When compared to other non-parametric algorithms, such as ANN, the computation time is quite short. While the access to an important training database is a barrier within machine learning, SVMs often perform well with sparse training data. Additionally, NIST is currently building use cases for typical industrial processes to aid in prognosis and health management research [29].

2.4 Hidden Markov Model

The Hidden Markov System is a variant of the Markov chain process that is employed to determine the probabilities distributions of state transitions and quantification of the results within a complex process in the presence of non - observable variables [30]. The HMM technique was employed to diagnose faults in both continuous and discrete production processes. [30-31] developed a novel multi-way discrete hidden Markov model (MDHMM) for FD and categorization in dynamic batching or semi-batch manufacturing techniques including inherent system uncertainties within the continual case. [29-31] used the suggested MDHMM method to classify various types of process defects with great accuracy in a fed-batch penicillin fermentation process. [32] used HMM to detect and diagnose instrument durability and ball bearings problems in the discrete instance. The algorithm accurately identified the device's status (i.e., sharp, worn, or broken) and the severity of the defect seeded in two distinct engine bearings [32]. Along with the severity rating, a localization index was developed to indicate the position of the fault (inside race, ball, or outside race) [32].

As with the analogue sensor system employed in conjunction with ANNs, [6-30] employed HMMs in conjunction with sophisticated signal processing techniques to determine the cause of a ball bearing defect. The algorithm was based on Swarm Rapid Centroid Estimation (SRCE) and HMM, and the defect frequency signatures were extracted using Wavelet Kurtosis and Cepstral Liftering to achieve an average sensitivity, specificity, and error rate of 98.02 percent, 96.03 percent, and 2.65 percent, respectively, on bearing fault vibration data provided by Case School of Engineering, Case Western Reinsurance Company. HMM is a probabilistic model that excels in modeling processes with unobservable states, such as chemical processes or the health status of equipment, making it a great fit for FD. However, training is often a computationally demanding procedure [21].

C. Contemporary Patterns Regarding Development on Machine Learning

Machine-learning scientific study is making major strides in a variety of domains. Hence, the present section addresses two of the most significant trends and certain relevant issues. Ramping up machine-learning techniques and learning numerous models are the two major ways.

1. Extending the reach of machine-learning techniques

Massive quantities of data are gathered in information management system and information repositories in contemporary manufacturing settings from fields such as process optimisation, product development, production planning and control, and maintenance. The first important field of research involves strategies for ramping up machine-learning techniques ensuring how they could efficiently analyze a huge data sets whilst generating the best potential models from them. The rapid surge of big data as a significant application of machine-learning techniques highlights the importance of algorithms being capable of handling huge information sources that are now further than their capability. Dataset contains containing billions of training samples, dozens of variables, and thousands of categories are typical within data mining applications. [8] identified numerous sample datasets comprising hundreds of terabytes of information. Developing learning techniques that are suitable for these kind of applications is therefore becoming a prominent research area.

Numerous techniques to ramping up machine-learning algorithms were proposed and applied [29–30]. The simplest solution is to create more optimization techniques or to increasing the effectiveness of current algorithms. This method encompasses a broad range of algorithm design strategies for improving the research and encoding, for obtaining approximation rather than precise results, and for using the task's constant process. A second option is to split the information, which avoids the requirement for algorithms to be performed on extremely big datasets. This strategy entails segmenting the information number of clusters, learning from several of the groupings, and integrating the findings. Information segmentation is advantageous because it helps prevent issues related to managing memory, which arise when algorithms attempt to analyze large data sets within the main memory [13]. An method that is complementary to the choice of case groupings is to concentrate on subgroups of important characteristics.

To offer context and specific detail, the deployment of inductive learning approaches to quite huge datasets is now explored; the challenges and solutions mentioned apply to other forms of machine learning as well. Numerous improvements have been made to the decision-tree procedures to enable them to manage large volumes of data effectively, and numerous new methods have been suggested. Catlett offered two approaches for reducing the time required to create a classifiers [9-10]. The very first technique collected information at every decision tree point, whereas the second approach fuzzified continuum features. Such techniques greatly reduce classification time and moreover diminish classification accuracy. Additionally, Catlett evaluated only sets of data which could be stored within primary computer memory. [28–32] discusses methods for dividing the data stream in such a way that each portion resides within main memory. While these approaches allow categorization of huge datasets, their research indicates that the resultant decision tree is of lower quality than a classifier created utilizing the entire data set at once. Additionally, incremental-learning approaches have been investigated [11], in which data is categorized into batches. The accumulated costs of gradually categorizing data, on the other hand, can occasionally outweigh the cost of classifying the whole training set once.

The decision-tree classifier in [12], dubbed SLIQ, included innovative approaches such as pre-sorting, broadness development, and MDL-based trimming to reduce the classifier's learning time without compromising the performance. Simultaneously, these approaches enabled classification on massive quantities of disk-resident training data. Yet, because the SLIQ uses a recollection database schema, which increases with the classes in the training set, the maximum number of instances that could be analyzed is limited. [14] proposed SPRINT, a classification method that eliminates all memory constraints associated with the conventional decision-tree algorithms while exhibiting the same outstanding performance as SLIQ. SPRINT effectively classifies data sets of almost any size; moreover, the technique may be readily executed in parallel. SPRINT, on the other hand, has been questioned for a myriad of causes. For instance, it makes use of database systems termed characteristic listings that may be expensive to build and maintain, potentially resulting in a doubling of the data set's size and a corresponding substantial rise of scanning expense [15]. SLIQ and SPRINT, like C4.5, are two techniques that involve phases of construction and trimming. Producing the decision tree within two different stages may lead to significant work being squandered, because a whole subset of features created during the first stage might well be trimmed within the subsequent stage. PUBLIC [16] is a decision-tree classifier that strongly couples the trimming and constructing stages rather than doing them sequentially. Its tree-increasing phase is identical to SPRINT's, excepting that entropy is used instead of the Gini index. When a leaf node is created, however, PUBLIC can instantly determine if additional splitting is necessary by calculating the cost of coding the subtree rooted at this leaf node. PUBLIC's comprehensive approach can result in significant performance gains over conventional classifiers like as SPRINT.

[30] recently introduced Rain-forest, a framework for designing fast and effective algorithms for building decision trees that gracefully adjust to the amount of available main memory. Finally, Morimoto et al. [29] devised techniques for building decision trees with wide domains for categorical characteristics. This effort focuses on enhancing the quality of the resultant tree.

As with decision-tree learning, a variety of rule-induction techniques are capable of scaling to very large data sets. IREP [27] is a rule-learning algorithm that is capable of handling huge amounts of noisy data effectively. The primary reason for its effectiveness is because it employs a technique called incremental reduced error pruning, which prunes each rule immediately after it is induced, rather than after all rules are created. This accelerates the induction process since pruned rules allow for the removal of a larger subset of the remaining positive cases each iteration than non-pruned rules do. Regrettably, the accuracy of class descriptions learnt using IREP is frequently worse than that of class descriptions learned using the C4.5 rules method [1], a rule-inducing variation of C4.5. [18] described various changes to IREP aimed at increasing its accuracy, including a different rule-evaluation criterion, a different stopping condition, and a post-processing optimization operation, resulting in the method RIPPER. He demonstrated that RIPPER is error rate competitive with C4.5 regulations and retains the efficiency of IREP. RIPPER is capable of handling characteristics that are missing, continuous variables, and numerous classes. As a result, it may be applied to a broader range of benchmark issues.

D. Applications of Machine Learning Techniques in Manufacturing

The present section outlines certain applications related to the machine-learning within the manufacturing industry. To date, machine learning algorithms are domain-independent. They might, in principle, be an extremely helpful resource for promoting knowledge-based platforms. Attempts to use machine-learning techniques follow a consistent trend. The method is divided into five stages: formulation of the issue, definition of the representation, collection of training data, evaluation of acquired knowledge, and deployment of the knowledge base [29–30]. Machine learning has been effectively used to a broad variety of manufacturing applications. [31] presented an inductive-learning technique and utilized it to create a qualitative knowledge-base from simulated experiment data. Inductive learning was utilized to construct a comprehensive characterization on the ranges of the process parameter for a class (specified by the variables of the classification goal factors). By doing so, the produced knowledge-based may be used for deductive reasoning and process control. [8] investigated process-planning decision-making difficulties using inductive learning. They acquired information about steel mill processing pathways using a mixture of induction and interview data. Even though, the experts were relatively communicative, substantial time and energy were spared by assisting the specialists in standardizing and organizing their knowledge using the rule of induction.

Engineers have used inductive learning approaches to synthesize vast quantities of data to aid in decision making. An inductive-learning method was utilized to interpret data from turning-process simulations in support of manufacturing's machine operation planning [26]. [25-27] proposed a knowledge-processing technique that integrates the technical capabilities of modeling and optimisation with identifying patterns in data. The method of inductive learning was combined with multi-goal optimisation to create a system that offers scientists with customizable support throughout both the model generation and use stages. It is becoming highly essential in production information systems to build autonomous schedule solutions as production stages get more sophisticated. Learning-based scheduling, which entails the automated adoption of dispatched parameters, is a viable technique for resolving this issue. Numerous efforts have been made to apply learning to planning issues [19–20]. The proposed approaches for developing a planning regulations utilizing inductive learning have been used to stream scheduling issues [23], job-shop scheduling difficulties [24], and flexible production system scheduling challenges [29]. The experimental data revealed that the offered approaches are capable of achieving effective scheduling.

[30] developed an inductive-learning system based on the Machine learning that autonomously incorporated knowledge into an intelligent system to assist aircraft blade maintenance. algorithms were used to just-in-time manufacturing systems. To begin, neural network models and decision trees were employed to determine the quantity of kanbans in a dynamic JIT production lines [18]. The quantity of kanbans is critical to the efficient running of a JIT manufacturing system. The data suggest that neural network models and decision trees are two viable methods with the ability to constantly alter the amount of kanbans. Second, an inductive learning technique was utilized to forecast JIT manufacturing performance using historical data that included both excellent and unsatisfactory manufacturing performance [4]. The CART decision-tree classifier was used in instance to build guidelines dynamically within a just-in-time manufacturing process. The guidelines developed are capable of properly classifying and forecasting manufacturing performance based on workshop characteristics, as well as identifying critical ties between the shop elements that affect manufacturing performance. The findings show that inductive learning is a viable approach for forecasting JIT manufacturing performance using dynamic shop-floor data.

Reich highlighted the essential importance of machine-learning simulation within engineering design [25]. He demonstrated how machine-learning systems' information models abilities may be used to produce high-quality design concepts. [4] explored how machine-learning approaches may be used to solve the issue of steel ablation. They analyzed, classified, and predicted the quality of steel etchings using three distinct approaches. Artificial neural network, inductive learning, and case-based learning, a kind of instance-based learning, were used as methods. The findings showed that machine-learning approaches, with their capacity to evaluate and manage huge quantities of complex data in a variety of industrial processes, aid in reducing turnaround time and waste and optimizing resource usage.

Contemporary sensor-equipped devices, like airplanes, produce enormous quantities of quantitative and conceptual information during the operation and maintenance.[32] devised a method for utilizing this data to construct models for forecasting when and how to change key airplanes parts prior to failure. To deduce the necessary models, three distinct machine-learning approaches have been utilized: induction learning, example-based learning, and Bayesian learning.

Semi-conductor industrial production is a demanding process that requires continuous supervision of a huge number of factors from the first phases of production through the final product's packaging. Enhancing the production system's quality needs extensive data processing, which is still accomplished by experienced experts. A typical wafer manufacturing factory processes up to one million wafers per day [6]. Due to the volume of available data, the analysis of the data is a very demanding and complex process. Numerous scholars suggested methods for incorporating machine-learning techniques into semi-conductor production [7]. The findings of the research demonstrated that machine-learning approaches may be effective instruments for continuous improvement process within a big and complicated process like semi-conductor production. [31 built a smart data-mining method and used it to the study of wearable digital goods' drop-testing information in order to uncover important design information. The method of rule induction used is the Classifier technique. The suggested system's methodology is adaptable and may be used to a variety of other design and production operations in order to decrease costs and improve efficiency. [21] described an industrialized optical monitoring system for quality control purposes in large scale production. The design allows use of the RULES-3 algorithm for inductive learning. Peng [15] designed a smart surveillance system based on fuzzy inductive learning for increasing the efficiency of industrial operations. The approach has been successfully utilized to diagnose the state of tapping operations in order to assure product quality. [16] discussed how data mining and machine learning approaches were applied in a steel bar production firm. The program analyzed make-to-order (MTO) vs make-to-stock (MTS) orders, product sale profiles, rogue orders, late orders, and product combination orders. The findings established that the methodologies used may extract data to aid in intelligent decision making in industry. Other applications include developing decision rules for conceptual design of steel members subjected to bending [17], diagnosing engine faults [18], detecting manufacturing defects in disk drives [19], diagnosing motor pumps [8], analyzing non-destructive testing of spotweld quality [29], managing and controlling raw material procurement, and accelerating rotogravure printing.

1. Advantages of machine learning application in manufacturing

[29-30] argued that the basic advantages of machine learning have been shown in earlier sections, including the ability of machine learning approaches to tackle NP-complete issues that frequently arise while optimizing smart manufacturing systems. This section will discuss machine learning techniques' ability to manage high-dimensional, multidimensional data and their capacity to spot latent correlations from huge data sets within a complicated and evolving, sometimes volatile situation. Because the majority of engineering and industrial issues are information yet knowledge-scarce, machine learning offers a means of increasing the domain expertise [31]. The benefits are described in this article in an attempt at generalization for machine learning in general. Nevertheless, it must be recognized that the peculiarities of the benefits might vary based on the machine

learning approach used. In general, it is accepted that machine learning enables the reduction of cycle time and scrap, as well as the optimization of resource usage, in specific NP-hard manufacturing issues. Additionally, machine learning enables continual quality enhancement within an intricate system like semiconductor manufacturing.

One benefit of machine learning techniques is their capacity to manage issues and data with a high degree of dimension. This will almost certainly become much more critical in the future, given the rising availability of large information and the lack of openness in manufacturing. As is the case with the majority of the pros and downsides of machine learning methods, this cannot be extrapolated. Certain techniques (for example, SVM; Distributed Hierarchical Decision Tree) are better at dealing with large dimensionality than others. As previously stated, in manufacturing, machine learning algorithms able to manage large amounts of data that are primarily used [18]. As a result, the capacity to deal with high dimensionality is viewed as a benefit of machine learning applications in manufacturing. Another advantage of machine learning approaches is the improved accessibility of algorithms as a result of (often open source) applications such as Rapidminer. This enables (relatively) simple implementation in many instances, as well as convenient parameter modification to improve classification results.

As previously stated by [29-30-31] a significant benefit of machine learning algorithms is that they enable the discovery of heretofore unrecognized (inherent) information and the identification of inherent relationship issues within set of data. The requirements about existing data differ according to the attributes of the machine learning algorithm. Nevertheless, the overarching capability of the machine learning model to yield change within a factory setting has been demonstrated successfully.

Provided the vibrant, ambiguous, and sheer complexity of manufacturing technologies. In this, machine learning techniques enable the complex system to learn from its environment and adapt to it instantly and to some degree. The transformation is relatively quick, and in almost all cases faster than conventional methods, relying on the machine learning algorithm used. Implementing machine learning in industrial production might well lead to the derivation of patterns from available data, which could also serve as a basis for developing estimations concerning the system's future performance. Such a new knowledge could be used to assist key stakeholders in making decisions or to directly improve the system. Finally, some machine learning techniques attempt to identify some patterns or consistencies, which characterize the relationships. [30] evaluated by comparing a few algorithms based on their performance in various manufacturing applications. Although this provides an initial impression, it is not recommended to base the selection of the appropriate machine learning model purely on the analogies introduced in such a table. So every dilemma is unique, and each algorithm's performance is also dependent on the availability of data, information which was before, and parameterization. The optimal algorithm should be discovered through extensive testing in a realistic environment.

Additionally, supervised machine learning techniques are frequently used within manufacturing applications owing to the information and yet knowledge-scarce nature of the issues. Additionally, supervised machine learning might very well profit from existing information gathering procedures in manufacturing for statistical process control purposes and from the reality that most of these data are labeled. Essentially, supervised machine learning is "learning from scenario given by an experienced external supervisor". This is partially because (a) specialist feedback (– for example, quality) and (b) clearly labelled incidences are available. Supervised machine learning is used in a variety of industries, with industrial production, tracking, and control becoming a particularly prominent one [12-13].

The basic process of supervised machine learning entails several stages, including ability to handle the data and configuring the training and test data sets. The necessary information is collected and pre-processed depending on the nature of the issue. A critical component is the training set design, since it has a significant impact on the subsequent classification outcomes. Although it frequently does seem as though the algorithm classification is often dictated by the description of the datasets, the description of the testing dataset should also take the algorithm preference requirements into consideration [7]. Certain algorithms allow for a procedure termed as 'kernel selection' that accommodates the algorithm to the unique characteristics of the issue. This demonstrates the ability to adapt of machine learning applications and the breadth of issues that can be addressed. Related guidelines are applicable to a lesser degree to data identification and pre-processing, as existing algorithms have varying strong points and disadvantages when it comes to managing diverse data sets. After selecting an algorithm, it is trained on the training data set [9]. The trained algorithm is then evaluated against the evaluations data-set in order to determine its ability to perform the targeted task. Depending on how well the trained algorithm performs with the evaluation data-set, the parameters can be changed to enhance performance in cases when performance is already good. If the performance is not satisfactory, the procedure must be restarted at a previous step, based on the actual performance. As a general rule, 70% of the data set is used for training, 20% for evaluation (to adjust parameters such as bias), and 10% for testing. The next section discusses supervised learning algorithms in greater detail, as they are the most often employed algorithms in manufacturing today. A significant reason for this is the widespread availability of 'labels' based on quality checks in a variety of manufacturing applications [29].

E. Proposed Machine Learning Model

The propose an integrated machine learning model propose in this study was adapted from [12-21-29-30]. The mode is made of property-structure correlations in this section. The design approach may be employed to develop products with specified mechanical property distribution. Such material properties distribution would be obtained by component design customization, not through the use of various materials. The figure below illustrates the model within which this design technique operates. The proposed Machine learning model consists of four phases.

Phase 1: identify the appropriate design space. This involves defining the desired characteristics (– for example, the stress-strain reactions of an ankle brace) and the desired design factors (e.g., the geometric variables of horseshoe structure for ankle brace). Create a sampling method for the design space, and then simulate the mechanical characteristics of each sampled location. This will save the mechanical characteristics of components with varying geometries. The purpose of this stage is to collect sufficient data to construct a machine learning model [21-29].

Phase 2: Build the machine learning model. While selecting a machine learning (ML) fundamental structure (– for example, convolutional neural network (CNN), or deep neural network (DNN), the following criteria should be observed [21].

• If somehow the mechanical attribute must reflect a distribution; for example, the stress-strain curve must be exactly, a CNN can be used to construct the model. Since CNNs are extremely good in picture classification and identification, the image of the stress reaction, or any other desirable property distribution, may be utilized for training [46].

• If the required characteristic is based on a single or a few points rather than the whole stress-strain curve or other distribution (– for example, stress equals 11 MPa when strain equals 0.3 in orientation, hence a DNN may be utilized to construct the machine learning model. The link between precise inputs and outputs may be modeled as a regression issue that DNNs excel at solving [21].

Phase 3: after establishing the machine learning model, the needed mechanical characteristics may be utilized as input (points data for DNN, images for CNN). Then, the machine learning model may immediately produce the design's qualifying geometry [21].

Phase 4: Finally, the resulting component with the desired geometry may be submitted to an additive manufacturing facility for manufacture [21].

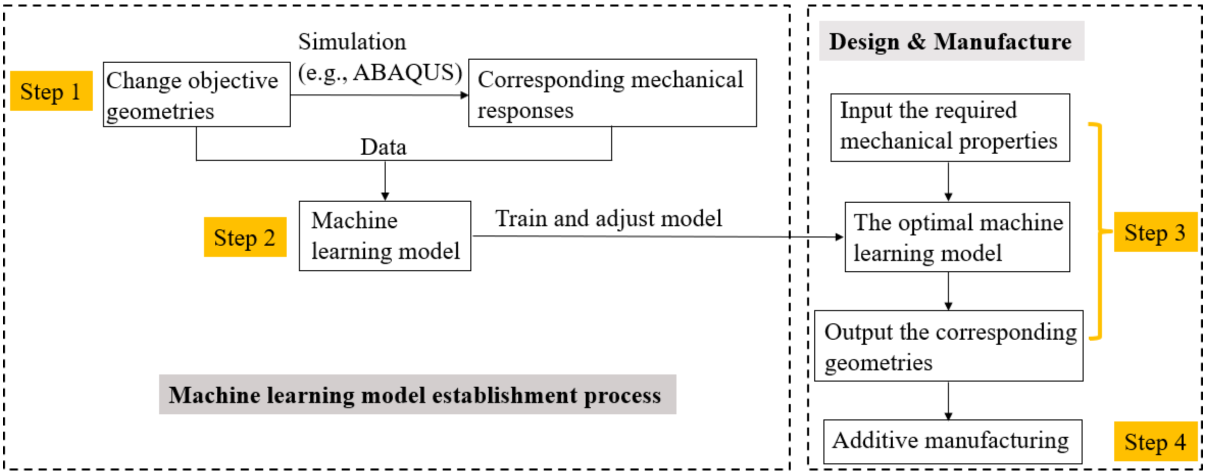

Figure 4: An integrated Machine Learning Model for Manufacturing industry [21]

As adapted from [12-21-29-30]; the proposed machine learning model is intended to resolve the previously mentioned operational issues by allowing the digitalisation, robotization, and connectivity of manufacturing systems, as well as by incorporating computer-aided initiatives and autonomous technology into production processes. Distributed intelligent and Internet-based platforms could offer 'artificially intelligent management,' that combines self-controlling technologies to manage organizations with a high degree of complexity. This capacity can substantially increase responsiveness and flexibility. In other words, businesses may realize significant efficiency gains by developing and implementing smart systems and technologies throughout their operating processes . Numerous businesses have recognized the potential benefits of Industry 4.0 enabler technologies and are investing heavily in sophisticated technology and robotics. According to PWC's 2016 worldwide Industry 4.0 study, the majority of businesses - around 60% - anticipate seeing a return on investment (ROI) within two years or less for their Industry 4.0 initiatives, while the remainder anticipate a ROI of around five years. Given the considerable advantages and long-term effect of sophisticated technical advances, a return on investment of between two and five years appears acceptable and feasible. The following sections describe the primary benefits of the proposed machine learning model as it can be seen in Figure 4.

A. Optimization of production efficiency

The application of the integrated Machine Learning Model in Manufacturing industry as shown in figure 4 above has the ability in:

- Optimizing the utilisation of resources and reducing the potential downtime
- Improving direct and indirect labor productivity
- Overseeing the expenses of supply chain and synchronization
- Assuring the accuracy and reliability of schedules and plans
- Discovering new growth opportunities for the core business
- Increasing aftermarket income streams
- Expanding consumer understanding and knowledge
- Improving customer integration and channel management
- Creation of novel items and service offerings
- Deepening globally and in emerging marketplace

B. Developing intelligent goods and/or services

With the application of the integrated Machine Learning Model in Manufacturing industry, Goods in the Era of industry 4.0 span the technical spectrum. The combination of Information Technologies such as sensors and wearables with advanced production techniques such as additive manufacturing, sophisticated computer numerical control, and robots can result in product enhancements. The Potential of Industry 4.0 applications for product transformation is presented in the below lines:

• Enhancing the effectiveness of pre-existing items: Incorporating sensing devices and interface to enhance performance of the product or safeness; connecting to smart devices to enhance the end-user experience; upgrading current goods with new materials to increase performance.

• Providing intelligent technology-generated data as a goods or services : Providing accessibility to data and analytics produced via current company activities; designing and offer in a platform for managing data from interconnected product lines; creating customized data packages for individual consumers.

• Creating brand-new products and services : Developing mass customisation at an affordable price; enabling novel and mixed innovative products using advanced production technology; build innovative service models and revenue streams.

Undoubtedly, companies have already been utilising advanced additive manufacturing and smart scanners and embedded sensors to develop novel products and enhance existing ones, therefore offering new degrees of value to consumers and additional data streams. In one such instance, operation technology and Information Technology are being utilized to mass customize medical devices that are required by a large number of people but each has its own unique design and conditions.

C. Engaging and incorporating consumers in innovative ways

The application of the integrated Machine Learning Model in Manufacturing industry. Manufacturers may gain a deeper understanding of their consumers by utilizing data and information acquired through smart goods and services. Certainly, consumer experience with in the age of Industry 4.0 is influenced not just by the physical item, however also by the information and data analytics, which make the consumer's engagement with the product more visible and have a variety of other effects on the customer-manufacturer relationship. Potential Industry 4.0 applications for customer transformation is presented in the lines below:

• Smartly market and sell items and services: Utilize data to enhance end-users intelligence; implement smart pricing models depending on inventories and user information; and utilize statistics to forecast consumers' necessity for spare parts.

• Enhance the post-purchase experience: Utilize data to monitor resource quality, and component and system failures in order to anticipate consumer demands and optimize availability; conduct fleet performance/operation analysis; and boost customer satisfaction via sensing applications.

• Maximize availability and efficiency: Utilization of data to connect the appropriate items with the right retailers at the right time to improve inventory management; monitor the consumption, effectiveness, and placement of goods remotely; improve product distribution

User information may be utilized to more rationally price and offer products and services. For example, the Deutsche Bahn, a European cargo rail consortium, for example, incorporated its huge system of railroad monitoring sensors with its consumer purchasing and invoicing dataset and provided factual data about congestion and capacity to produce smart pricing structures tailored to a client's needs and current conditions. 29 Uber, for its part, utilizes data from its drivers and consumers to fuel an algorithm that generates surge pricing, a dynamic pricing mechanism that adjusts costs upward in response to increased demand. 30

IT and OT have the ability to increase product and service quality, as well as asset usage intelligence. Additionally, this data may be used in both directions: it can be transmitted to the manufacturer and its partners, as well as returned to the consumer via smart apps that enhance the user experience. In one such instance, a pharmaceutical firm explored incorporating smart monitoring sensors into its inhaler product line in order to collect real-time data and analyze it in order to provide insights to both patients and clinicians. 31

D. Engineers: Advancing innovation and development cycle

With the application of the integrated Machine Learning Model in Manufacturing industry as illustrated in figure 4. Goods are designed and constructed at the beginning of the production life cycle. Numerous Industrial revolution 4.0 innovations such as additive/advanced manufacturing and information technology, as well as digital tools like as Computer - aided design and modeling can be used to significantly affect the process in a variety of ways.

• Reduce the time required to bring an innovation to market; Utilize fast prototypes and production capacity to create new goods and minimize supply chain reliance; setup new software solutions using cloud-based development tools.

• Improved connection between design and product intelligence: Utilize data to predict design problems and address them; design goods and simulate usage in terms of total cost of operation and supply chain ramifications; and assess product design choices in terms of manufacturing processes.

• Enhance the engineering profession's overall performance: Develop and try out new goods using digital simulation software; enable open source copyright sharing to inspire or enhance ideas

Rapid prototyping with digital-to-physical manufacturing technologies such as additive printing can accelerate both the design and manufacture of end-use goods, therefore decreasing supply chain dependency. For example, Ford believes that by utilizing fast prototyping during vehicle design, it may save weeks by fabricating prototypes in hours rather than the four to six weeks required by traditional machine tooling techniques, allowing vehicles to reach the market months sooner. Engineers can also maximize manufacturability by evaluating product design alternatives in light of the ultimate assembly process. Products are conceived and designed at the start of the manufacturing value chain. Numerous Industry 4.0 technologies—particularly operational technologies such as additive/advanced manufacturing and information technology, as well as digital tools like as CAD and simulation—can be used to significantly affect the process in a variety of ways.

E. Planning: Forecasting change and reacting to it in real time

When manufacturing companies prepare for production, they frequently confront a slew of uncertainty along the manufacturing value chain. Information Technology and Operation Technology can help facilitate a number of transformations in this area.

• Demanding sensors and planning: Gather and assess data to continuously monitor demand trends; follow products movement across the supply chain for demand planning reasons; and proactively recommend product replenishment to consumers as needed.

• Supply chain management and transformation of suppliers: Allow suppliers to monitor and control inventories in the Original equipment manufacturers supply chain; have a better knowledge of supplier capacity and lead times; and make better pricing decisions by utilizing external market information.

• Optimizing the outbound networks: Inventory tracking in forward networks; real-time route changes for distribution vehicles in response to unanticipated events; and the ability for consumers to follow delivery progress by precise location.

Demand sensing and planning via the use of information technology (for example, sensors, signal aggregation, optimization, and prediction) enables manufacturers to collect data across the value chain. Data analysis may be used to identify patterns, follow movement, and eventually understand what consumers want and where they want it—so businesses can plan more effectively to deliver it at the appropriate time and place.

F. Factory: Establishing a digital connection between operational and information technology

Maybe no other sector more exemplifies Industry 4.0's physical-to-digital transition than the smart manufacturing. Physical-to-digital technologies such as augmented reality, sensors and controls, wearables, and the Internet of Things enable the industry 4.0-enabled factory to track movement and production, monitor quality control, and manage the tooling life cycle, among other capabilities. Thus, Industry 4.0 on the factory floor can enable increased capability effectiveness, knowledge about production assets, and activity synchronization and flow.

- Increasing the productivity and efficacy of labor: Improve manufacturing and assembly abilities; labor productivity monitoring; employee mobility and efficiency monitoring; and real-time safety monitoring of both personnel and equipment.
- Intelligence on production assets: Proactive sensing and quality control are used to identify problems; predictive maintenance is used to maintain manufacturing machinery; and tooling life cycle management is used to manage tooling.
- Synchronization and flow of activities: Utilize technology to enable dynamic routing throughout the manufacturing process; conduct virtual build simulations to determine the efficacy of engineering modifications to the production floor; and accommodate variable environmental elements that may affect machines.

Industrial revolution 4.0 technology can improve worker safety while also increasing labor productivity and effectiveness. Joy Global, a producer of mining equipment, equipped its remote-controlled extraction gear with over 7,000 sensors, enabling it to dig in incredibly deep mineshafts—areas that are frequently perilous for the personnel who normally conduct the operation. Similarly, Boeing employs a positioning system to determine the location of workers and to monitor the condition of their safety harnesses, therefore increasing worker safety. Beyond labor productivity and safety, Information system may alter the intelligence of product assets. Harley-Davidson, for instance, employs intelligent technologies to detect problems throughout manufacturing processes. In its York, Pennsylvania, factory, a smart system analyses equipment performance and takes action autonomously. When measurements are detected to be outside of permissible ranges, the machinery is immediately modified to avoid problems.

F. Conclusion

Digital technology has increasingly penetrated into the manufacturing and industrial operations over the last decade. Significant advancements in the realms of the Internet of Things, Cloud Computing, drones, blockchain technology, sensors, machine learning have impacted the manufacturing sector significantly. This once-in-a-generation phenomenon, frequently referred to as "the Industry 4.0," has acquired significant pace. Industrial revolution 4.0 has the potential to fundamentally alter how things are designed, manufactured, and used, while also catalysing the emergence of new marketing strategies, products, and practices. Whilst Fourth industrial revolution has several potential for economic growth, its long-term implications are largely unknown. Fourth industrial revolution emanates in the context of trying to press the worldwide issues such as global warming, food shortages, inaccessibility to electricity, water shortages, ecological degradation, and resource depletion, as well as emerging trends such as population growth, urbanization, and massive immigration, and also current and longstanding conflicts and crises globally. This poses the problem of whether – and how – Fourth industrial revolution might help to the development of novel approaches to deal with certain key social, economic, and environmental concerns.

To this end, the manufacturing sector is undergoing numerous changes. Production process, sophisticated material, intelligent, computerized equipment, and other breakthroughs are entering into a new era of large scale manufacturing. Simultaneously, improved connectivity and incredibly advanced data collection and analytics capacities afforded by the Industry 4.0 technologies have accelerated the transition to a data-based economy. with industry 4.0 physical items, data is a source of value in the Internet of things connectivity enables the creation of intelligent supply chain operations, manufacturing techniques, and even end-to-end environments. While these winds of innovation continue to influence the market environment, decision makers in manufacturing sector should decide when and where to adapt to new technologies, including which options can yield the highest return on investment for their companies. Along with accurately measuring their existing key points, effective manufacturing companies should therefore articulate their business goals clearly, pinpointing where to function in emerging digital environment and, more importantly, what types of technology, both physical and virtual, they might very well implement in order to pursue their winning decisions. Notwithstanding the hoopla surrounding sophisticated physical and virtual advancements, few studies have been conducted in this regards. Similarly, numerous stakeholders are unsure of the implications of all this connection for their businesses — and for the wider manufacturing environment. Nevertheless, one thing is certain: underestimating the critical importance of information flow play in the physical components of smart factories would be a mistake. To fully exploit the benefits presented by both the physical and virtual worlds, it is critical to integrate them—to leverage digital data from a variety of sources and locations to drive the physical act of manufacturing. In other words, integrate the industry 4.0 technologies and operations technology to build a more robust manufacturing establishment. Further, in order to counteract the current ever-growing worldwide competition regarding products quality and production overheads, as well as the necessity for production flexibility, call for the transformation of manufacturing system in order to allow a higher degree of functionality and synergy across business operations. Most of traditional computer-integrated initiatives and modern manufacturing systems remain constrained and apply to only a subset of organizational functions. This narrow capacity that results from the lack of interconnectivity and synchronization among production and enterprise systems, prevents those technologies from reaching their full potential in the production. Hence, machine learning as a subset of Artificial Intelligence, has the potential to establish a foundation for tackling integration challenges by offering extensive interconnectivity. Thus, this study develops an integrated machine learning model applicable to manufacturing industry. The proposed model has the potential of Optimization of production efficiency; Establishing a digital connection between operational and information technology; Forecasting change and reacting to it in real time; Advancing innovation and development cycle; Engaging and incorporating consumers in innovative ways; Developing intelligent goods and/or services.

G. References

[1] A. Chawla, A. Singh, A. Lamba, N. Gangwani, U. Soni, Demand forecasting using artificial neural networks—a case study of american retail corporation, in: Applications of Arti- ficial Intelligence Techniques in Engineering, Springer, 2019, pp. 79–89.
[2] Aksoy, M. S., Torkul, O., and Cedimoglu, I. H. An industrial visual inspection system that uses inductive learning. J. Intell. Mfg, 2004, 15, 569–574.
[3] Akyol, D. E. Application of neural networks to heuristic scheduling algorithms. Comp. Indust. Engng, 2004, 46, 679–696.
[4] Apte´, C., Weiss, S., and Grout, G. Predicting defects in disk drive manufacturing: a case study in high- dimensional classification. In Proceedings of the 9th IEEE Conference on Artificial Intelligence Applications, New York, 1993, 212–218, CAIA-93.
[5] Aytug, H., Bhattacharyya, S., Koehler, G. J., and Snow- don, J. L. A review of machine learning in scheduling. IEEE Trans. Engng Mgmt, 1994, 41(2), 165–171.
[6] C. E. S. da Silva, E. G. Salgado, C. H. P. Mello, E. da Silva Oliveira, F. Leal, Integration of computer simulation in design for manufacturing and assembly, International Journal of Production Research 52 (2014) 2851–2866.
[7] Chand, S., & Davis, J. F. (2010, July). What is smart manufacturing? Time Magazine.
[8] Charniak, E.: Bayesian networks without tears. AI Magazine 12(4), 50 (1991).
[9] Chatterjee, A., Croley, D., Ramamurti, V., and Chang, K.-Y. Application of machine learning to manufacturing: results from metal etch. In Proceedings of the 19th IEEE/CPMT International Electronics Manufac- turing Technology Symposium, Austin, Texas, 1996, pp. 372–377.
[10] Cooper, G.: The computational complexity of probabilistic inference using Bayesian belief networks. Artificial Intelligence 42(2-3), 393-405 (1990).
[11] Correa, M., Bielza, C., Pamies-Teixeira, J.: Comparison of Bayesian networks and artificial neural networks for quality detection in a machining process. Expert Systems with Applications 36(3), 7270-7279 (2009).
[12] D T Pham* and A A Afify. 2005. Machine-learning techniques and their applications in manufacturing. Proc. IMechE Vol. 219 Part B: J. Engineering Manufacture
[13] D. Wu, C. Jennings, J. Terpenny, R. X. Gao, S. Kumara, A comparative study on machine learning algorithms for smart manufacturing: tool wear prediction using random forests, Journal of Manufacturing Science and Engineering 139 (7) (2017).

[14] Demetgul, M.: Fault diagnosis on production systems with support vector machine and decision trees algorithms. The International Journal of Advanced Manufacturing Technology 67(9-12), 2183-2194 (2013).
[15] El Attar, M. and Hamery, X. Industrial expert system acquired by machine learning. Applic. Artif. Intell., 1994, 8(4), 497–542.
[16] Elangovan, M., Sakthivel, N. R., Saravanamurugan, S., Nair, B. B., & Sugumaran, V. (2015). Machine learning approach to the prediction of surface roughness using statistical features of vibration signal acquired in turning. Procedia Computer Science, 50, 282–288. doi:http://dx.doi.org/10.1016/j. procs.2015.04.047
[17] Fernando, H., Surgenor, B.: An unsupervised artificial neural network versus a rule-based approach for fault detection and identification in an automated assembly machine. Robotics and Computer-Integrated Manufacturing 43, 79-88 (2017).
[18] G. Heddy, U. Huzaifa, P. Beling, Y. Haimes, J. Marvel, B. Weiss, A. LaViers, Linear temporal logic (ltl) based monitoring of smart manufacturing systems, in: Annual Conference of the Prognosticcs and Health Management Society, volume 6, PHM Society, 2015, p. 10.
[19] I. H. Garbie, DFSME: design for sustainable manufacturing enterprises (an economic viewpoint), International Journal of Production Research 51 (2013) 479–503.
[20] J.-L. Loyer, E. Henriques, M. Fontul, S. Wiseall, Comparison of machine learning methods applied to the estimation of man- ufacturing cost of jet engine components, International Journal of Production Economics 178 (2016) 109–119.
[21] Jingchao Jiang, Yi Xiong, Zhiyuan Zhang, David Rosen, "Machine learning integrated design for additive manufacturing", Journal of Intelligent Manufacturing, 2020.
[22] K. Hansson; S. Yella; M. Dougherty; H. Fleyeh, Machine learning algorithms in heavy process manufacturing. American Journal of Intelligent Systems 6(1) (2016), pp. 1-13.
[23] K.-D. Thoben, S. A. Wiesner, T. Wuest, "industrie 4.0" and smart manufacturing a review of research issues and application examples, International Journal of Automation Technology 11 (2017) 4–16.
[24] L. Scime, J. Beuth, Using machine learning to identify in-situ melt pool signatures indicative of flaw forma- tion in a laser powder bed fusion additive manufacturing process, Additive Manufacturing 25 (2019) 151–165. doi:10.1016/j.addma.2018.11.010.
[25] M. Helu, T. Hedberg, Enabling Smart Manufacturing Research and De- velopment using a Product Lifecycle Test Bed, volume 1 of Procedia Manufacturing, Elsevier Science Bv, Amsterdam, pp. 86–97.
[26] M. W. Gardner, S. Dorling, Artificial neural networks (the multilayer perceptron)—a review of applications in the atmo- spheric sciences, Atmospheric environment 32 (14-15) (1998) 2627–2636.
[27] S.-j. Wu, N. Gebraeel, Y. Yih, A neural network integrated decision support system for condition-based optimal predictive maintenance pol- icy, IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans 37 (2007) 226–236.

[28] T.-H. Yeh, S. Deng, Application of machine learning methods to cost estimation of product life cycle, International Journal of Computer Integrated Manufacturing 25 (2012) 340–352.
[29] Thorsten Wuest, Daniel Weimer, Christopher Irgens & Klaus-Dieter Thoben (2016) Machine learning in manufacturing: advantages, challenges, and applications, Production & Manufacturing Research, 4:1, 23-45, DOI: 10.1080/21693277.2016.1192517
[30] Toyosi Ademujimi, Michael Brundage, Vittaldas Prabhu. A Review of Current Machine Learning Techniques Used in Manufacturing Diagnosis. IFIP International Conference on Advances in Produc- tion Management Systems (APMS), Sep 2017, Hamburg, Germany. pp.407-415, 10.1007/978-3-319- 66923-6_48 . hal-01666171
[31] W. An, Y. Sun, D. Wang, Study on support vector machine in calculating steel quenching degree, in: 2006 6th World Congress on Intelligent Control and Automation, Vol. 2, IEEE, 2006, pp. 7780–7783.
[32] Y. Luo, K. Li, Y. Li, D. Cai, C. Zhao, Q. Meng, Three-layer bayesian network for classification of complex power qual- ity disturbances, IEEE Transactions on Industrial Informatics 14 (9) (2018) 3997–4006. doi:10.1109/tii.2017.2785321. URL https://doi.org/10.1109/tii.2017.2785321
[33] García-Ordás, M., "Wear Characterization of the Cutting Tool in Milling Processes Using Shape and Texture Descriptors," Ph.D. Thesis, Universidad de León, 2017.
[34] Cho, S., Asfour, S., Onar, A., and Kaundinya, N., "Tool Breakage Detection Using Support Vector Machine Learning in a Milling Process," International Journal of Machine Tools and Manufacture, Vol. 45, No. 3, pp. 241-249, 2005.
[35] Wu, D., Jennings, C., Terpenny, J., Gao, R. X., and Kumara, S., "A Comparative Study on Machine Learning Algorithms for Smart Manufacturing: Tool Wear Prediction Using Random Forests," Journal of Manufacturing Science and Engineering, Vol. 139, No. 7, Paper No. 071018, 2017.
[36] Park, J., Law, K. H., Bhinge, R., Biswas, N., Srinivasan, A., et al., "A Generalized Data-Driven Energy Prediction Model with Uncertainty for a Milling Machine Tool Using Gaussian Process," Proc. of American Society of Mechanical Engineers on International Manufacturing Science and Engineering Conference, Vol. 2, Paper No. MSEC2015-9354, 2015.
[37] Benkedjouh, T., Medjaher, K., Zerhouni, N., and Rechak, S., "Health Assessment and Life Prediction of Cutting Tools Based on Support Vector Regression," Journal of Intelligent Manufacturing, Vol. 26, No. 2, pp. 213-223, 2015.
[38] Bhinge, R., Biswas, N., Dornfeld, D., Park, J., Law, K. H., et al., "An Intelligent Machine Monitoring System for Energy Prediction Using a Gaussian Process Regression," Proc. of IEEE International Conference on Big Data, pp. 978-986, 2014.
[39] Huang, P. B., Ma, C.-C., and Kuo, C.-H., "A PNN Self-Learning Tool Breakage Detection System in End Milling Operations," Applied Soft Computing, Vol. 37, pp. 114-124, 2015.
[40] Klancnik, S., Brezocnik, M., and Balic, J., "Intelligent CAD/CAM System for Programming of CNC Machine Tools," International Journal of Simulation Modeling, Vol. 15, No. 1, pp. 109-120, 2016.

[41] Lu, X., Hu, X., Wang, H., Si, L., Liu, Y., and Gao, L., "Research on the Prediction Model of Micro-Milling Surface Roughness of Inconel718 Based on SVM," Industrial Lubrication and Tribology, Vol. 68, No. 2, pp. 206-211, 2016.
[42] Peng, C., Wang, L., and Liao, T. W., "A New Method for the Prediction of Chatter Stability Lobes Based on Dynamic Cutting Force Simulation Model and Support Vector Machine," Journal of Sound and Vibration, Vol. 354, pp. 118-131, 2015.
[43] Krishnakumar, P., Rameshkumar, K., and Ramachandran, K., "Tool Wear Condition Prediction Using Vibration Signals in High Speed Machining (HSM) of Titanium (Ti-6Al-4V) Alloy," Procedia Computer Science, Vol. 50, pp. 270-275, 2015.
[44] Arnold, F., Hänel, A., Nestler, A., and Brosius, A., "New Approaches for the Determination of Specific Values for Process Models in Machining Using Artificial Neural Networks," Procedia Manufacturing, Vol. 11, pp. 1463-1470, 2017.
[45] Yuan, Y., Zhang, H.-T., Wu, Y., Zhu, T., and Ding, H., "Bayesian Learning-Based Model-Predictive Vibration Control for Thin- Walled Workpiece Machining Processes," IEEE/ASME Transactions on Mechatronics, Vol. 22, No. 1, pp. 509-520, 2017.